Modeling fuels and wildfire behavior in Hawaiian ecosystems

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ABSTRACT

The interactions of nonnative invasions and landscape disturbances on novel fuel beds exacerbate the impacts of wildfire in Hawaii, and throughout the tropical Pacific Islands. Intensive field sampling and hybrid remote sensing techniques are valuable means of assessing regional and local variability in fuels in response to environmental gradients and management actions. The first chapter of this thesis introduces the context of these challenges, and provides a brief study overview. The second chapter seeks to understand the effects of nonnative feral ungulate removal, as well as the effects of ecological restoration, on fuels and modeled wildfire behavior in Hawaiian terrestrial ecosystems along a precipitation gradient. I sampled fuel characteristics inside and outside of 13 ungulate exclosures across a 2740 mm mean annual precipitation (MAP) gradient, and used linear mixed effects modeling to identify environmental and management drivers of fuel dynamics and modeled wildfire behavior. Fine fuel loads increased after ungulate exclusion (up to 11.3 Mg ha^{-1}), and increased in magnitude with MAP. Fuel load differences resulted in higher intensity modeled wildfire behavior (up to 1.9 m difference in flame length), which also increased in magnitude with MAP. Ecological restoration of sites following ungulate removal, however, decreased fine fuel loads over time by as much as 41% after ten years. Results from the second chapter demonstrate a clear trend in increased fuel loads after ungulate removal across a wide precipitation gradient, and point towards the need for effective fuels management strategies, such as long-term active ecological restoration, to reduce fuel loads and invasive species cover so as to break the positive feedback between nonnative invasions and wildfires. The third chapter of this thesis evaluates the accuracy of landscape fuel mapping by the national geospatial fuels product LANDFIRE versus a custom mixed methods approach that utilized supervised classification of field sampled fuel data, biophysical predictors, and remote sensing over a heterogeneous, dry tropical montane landscape in Hawaii. The custom fuel map demonstrated only a 27% agreement with the standard LANDFIRE fuel map, but had a 58% overall mapping accuracy which compares favorably with mapping accuracies from other fuel studies. In line with previous research in temperate ecosystems, my analysis indicates LANDFIRE can provide a first approximation of fuel conditions and wildfire risk for understudied regions, but that supervised classification of local fuels data, biophysical predictors, and remote sensing can greatly improve accuracy and utility. In the final chapter, I offer suggestions for negotiating tradeoffs between conservation, restoration, and limited wildfire suppression resources. Results from both data chapters demonstrate that fuel loads in Hawaii are highly variable, even within similar vegetation types, and substantially driven by climate, land use, disturbance history, and management actions. Limiting wildfire risk in the Hawaiian Islands requires effective fuel reduction treatments after nonnative feral ungulate removal, particularly in mesic and wet areas, as well as continued calibration of fuel maps.

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Chapter 1: Introduction

This thesis explores pressing questions in wildfire management in the Hawaiian Islands with implications for the tropical Pacific Island Region. Global wildfire activity poses a significant risk to human health and safety (Bowman et al. 2017), biodiversity (D'Antonio and Vitousek 1992), watershed conservation (Sankey et al. 2017, Trauernicht et al. 2018), primary productivity (Hawbaker et al. 2017), and other ecosystem goods and services (Moritz et al. 2014). Compared to the continental United States, the fire ecology of the Hawaiian Islands is an understudied subject. The current conditions and factors shaping Hawaiian fire ecology are distinct from the continental United States, as are its historic and predicted trajectories (Trauernicht et al. 2015). However, the risks and ecological impacts posed by wildfire in Hawaii are substantial and merit additional research. A better understanding of how the fuels that drive wildfire in Hawaii are affected by the management of nonnative feral ungulates and by ecological restoration, as well as the improved mapping of wildland fuels at the landscape level, will inform conservation, restoration, and wildfire management efforts for the region.

Wildfire in Hawaii

Native ecosystems globally are increasingly challenged by novel wildfire regimes driven by both nonnative species invasions and landscape-scale disturbances (Hughes et al. 1991, Litton et al. 2006, Krawchuk et al. 2009, Jolly et al. 2015). The contemporary wildfire regime in Hawaii, for example, is characterized by a substantial increase in the extent of area burned over the past 100 years, with much of it accelerated by the widespread invasion of fire-prone and fire-adapted nonnative grasses and shrubs (D'Antonio and

Vitousek 1992, Trauernicht et al. 2015). The introduction of rapidly regenerating and pyrophilic nonnative species, often through the clearing of land for agriculture and ranching, has created a feedback effect in which the margins of native ecosystems are threatened by a continually present novel fuel source (D'Antonio and Vitousek 1992). Even in many remnant native forests, understories are heavily invaded by nonnative grasses such as *Cenchrus setaceus* (Forssk.) Morrone (fountain grass), which limits recruitment and growth of native species through competition for resources, disruption of successional processes, and provision of ample fuels for wildfires (Litton et al. 2006, Thaxton et al. 2010, Adkins et al. 2011). Additionally, although native species in Hawaii possess adaptations to disturbances, including wildfire, nonnative species have demonstrated increased capacity for recovery and invasion following wildfires (Ainsworth and Kauffman 2009). Native species, as a result, are at greater risk of extirpation due to wildfire relative to nonnative species (Smith and Tunison 1992, Ainsworth 2007).

Despite increased investments in wildfire management (e.g., suppression, fuel reduction treatments, fire-resilient infrastructure, and public outreach/education), mitigating wildfire risk and identifying better methods for allocating limited wildfire management resources remains a significant challenge (Stephens and Ruth 2005). The most typical means of reducing wildfire hazard and severity in the continental United States is through the manipulation and reduction of wildland fuels, or the dead and live biomass available for fire ignition and combustion (Keane et al. 2001), which is commonly accomplished via mechanical thinning or prescribed fire (Fule et al. 2001, Pollet and Omi 2002, Stephens et al. 2009). The management of wildland fuels in Hawaii is complicated, however, by novel and understudied fuel beds, climatic and topographic heterogeneity over short spatial scales (Trauernicht 2019), and the widespread presence of numerous introduced nonnative feral ungulate species that likely have important, but largely unknown, consequences for fuels management (Chynoweth et al. 2013, Hess 2016, Wehr et al. 2018).

Nonnative feral ungulates and fuels

Domesticated cattle (*Bos taurus*), goats (*Capra hircus*), sheep (*Ovis aries*), axis deer (*Axis axis*), and Polynesian, domestic, and wild European pig varieties (*Sus scrofa*) have been introduced to Hawaii over the course of prior centuries, and have established widespread feral populations throughout Hawaii, in addition to many other Pacific Islands (Hess 2016). These invasions cause substantial ecological degradation through the direct effects of herbivory, browsing, trampling, and bark stripping, as well as indirect effects via alterations in ecosystem processes such as hydrology and nutrient cycling (Cole and Litton 2014, Long et al. 2017, Wehr et al. 2018). From a wildfire standpoint, these invasions can reduce fuel loads and increase the discontinuity of the fuel bed (Kellner et al. 2011), but also facilitate nonnative species and alter vegetation cover (Courchamp et al. 2003, Parker et al. 2006), with important implications for the occurrence and spread of wildfires. The presence of introduced feral water buffalo in Northern Australian savannas, for example, has been observed to reduce wildfire probability (Trauernicht et al. 2013). Conversely, although nonnative feral ungulates are considered incompatible with native species conservation in Hawaii and throughout the Pacific Island region, carefully targeted and managed ungulate grazing is a potentially beneficial strategy with demonstrated success in reducing fuel loads and modeled wildfire behavior, at least over the short-term (Blackmore and Vitousek 2000, Leonard et al. 2010, Evans et al. 2015).

The widespread ecological impacts of nonnative feral ungulates have led to the fencing and removal of ungulates as an increasingly common management strategy for conserving and restoring native biodiversity (Zavaleta et al. 2001, Cole and Litton 2014, Hess 2016). Over the past 30 years, management agencies in Hawaii have fenced and removed nonnative feral ungulates from >750 km^2 of public land (Hess 2016). These efforts have been highly effective at reducing ungulate densities within management units, with important conservation benefits in most cases. However, at many sites ranging from dry to wet environments, nonnative feral ungulate removal can increase the cover of both native and nonnative plants due to release from top-down control, particularly at sites with substantial nonnative presence at the time of ungulate removal (Stone et al. 1992, Cabin et al. 2000, Kellner et al. 2011, Weller et al. 2011, Cole et al. 2012).

The interactions that ungulate removal may have with wildland fuels and wildfire behavior remain largely unquantified, particularly on tropical Pacific Islands. Past studies have focused on the effects of domestic grazing on fuels, the effects of nonnative feral ungulates on fuels in temperate ecosystems such as in the continental United States, or on the many effects of nonnative feral ungulates on ecosystem processes. Wildfire and herbivores are competing "alternative consumers" of vegetation (Bond and Keeley 2005), and similar to wildfire, the magnitude of ungulate removal effects potentially depends on moisture availability. For example, an Australian study of managed grasslands found that five to ten years after removing grazing herbivores, including deer, kangaroos, rabbits, and sheep, phytomass increased by an average of 737%, and mean annual precipitation (MAP) accounted for 42% of the variation in observed phytomass accumulation (Schultz et al. 2011). In contrast, Koppel et al. (1996) observed that in systems of high productivity in the Netherlands, grazing pressure did not keep pace with plant growth, such that there was little difference in phytomass in the presence of herbivores. Moreover, Leonard et al. (2010) found that low moisture at grazing sites was a constraint on grassland fuel accumulation, even with relatively low grazing pressure. Taken together, the body of current research suggests that moisture availability serves as an important regulator in the interaction between ungulates and wildland fuels.

Nonnative feral ungulates and ecological restoration

A potential mechanism to reduce fuels following ungulate removal lies in ecological restoration (e.g., outplanting of native species, nonnative plant control, alteration of resource availability). Active ecological restoration after the fencing and removal of ungulates is a common critical early step in the management of degraded sites (Banko et al. 2014). However, little is known about how this practice affects fuel loads or the potential for wildfire. At degraded sites, fencing without active ecological restoration can result in a substantial increase in nonnative species that interferes with the regeneration of native species, as has been shown in dry and mesic systems in the Hawaiian Islands (Cabin et al. 2000, Weller et al. 2011). Such studies indicate that fencing without active ecological restoration is not enough to achieve the conservation objectives of returning an ecosystem to a native reference ecosystem.

Active ecological restoration has been shown to be useful for reducing fuel loads and wildfire risk. Ellsworth et al. (2015) demonstrated in experimental trials in highly degraded sites in leeward Oahu, Hawaii that after 27 months of active restoration (i.e., the combination of native species outplanting and herbicide application on nonnative grasses), invasive grass fuel loads were reduced by as much as 82%. However, other crucial fuel characteristics such as continuity and moisture content did not respond to restoration over the short term. As such, ecological restoration after nonnative feral ungulate removal can potentially be used as a mitigation tool for fuel loading and wildfire risk, while achieving other prioritized management goals such as native species conservation (Cabin et al. 2002, Daehler and Goergen 2005). Potential mechanisms for reductions of fuel loads through ecological restoration include the direct suppression of nonnative species with herbicide application, and competition from native species through alterations of nutrient availability and shading (Freifelder et al. 1998, Thaxton et al. 2012). Given high initial investment costs in restoration projects (Powell et al. 2017, Wada et al. 2017), understanding the impact of restoration on fuels and wildfire after ungulate removal over longer time periods (e.g., > 5 years) is critical to informing management decisions.

Mapping fuels in Hawaii

Making informed decisions on the management of wildfire-prone landscapes requires accurate and precise fuel maps, which can support efficient allocation of resources for fuel reduction treatments and safe wildfire suppression activities when fires do start. The most significant effort to project fuel characteristics across regional to continental scales is the Landscape Fire and Resource Management Planning Tools Program (LANDFIRE), which provides regional-scale geospatial data on vegetation, wildland fuel, and wildfire regimes across the United States. LANDFIRE's fuel products are particularly valuable for modeling wildfire but have not been validated in Hawaii, compromising their utility for management applications.

The scale of fuel mapping efforts, more generally, range from local (Francesetti et al. 2006, Krasnow et al. 2009), to regional and continental (Rollins and Frame 2006), to global (Krawchuk et al. 2009). At the local scale of a wildfire management unit, fuel maps can be developed from intensive field-based collection of vegetation characteristics, with resulting fuel maps used to predict actual wildfire behavior (Pierce et al. 2012). Because detailed on-the-ground fuel mapping efforts are resource intensive, as has been shown in temperate systems (Krasnow et al. 2009, Pierce et al. 2012), larger-scale fuel mapping efforts frequently rely on hybrid approaches that include data from a variety of sources including vegetation plots in the field and high resolution remote sensing such as Landsat and LIDAR (Keane et al. 2001, Arroyo et al. 2008).

One of the most widely used LANDFIRE products is the spatial assignment of the Scott and Burgan Fire Behavior Fuel Models (Scott and Burgan 2005), a set of surface fuel models that describe a particular area based on its dominant fire carrying fuel type. Fuel types are assigned to a particular model in the LANDFIRE product based on a combination of field data, image interpretation, remote sensing, and expert knowledge. The subjective nature of expert opinion and image interpretation can result in assignment errors and uncertainty that are largely unquantified, limiting the utility of LANDFIRE products, particularly at local scales. For example, Keane (2013) compared LANDFIRE spatial fuel products (Fuel Loading Models and Fuel Characteristic Classification System) with Forest Inventory and Analysis surface fuel estimates in the Western United States and found poor mapping accuracies primarily due to high variability in fuel loads within fuel model components that translated to inaccurate fuel model assignments. Krasnow et al. (2009) found that custom fuel maps produced through Classification and Regression Trees modeling of field plot data and local biophysical variables predicted the burned area of two historic fires more accurately than the corresponding LANDFIRE maps, primarily due to improved modeling of understory fuel components.

Uncertainty in fuel mapping can result from a lack of accuracy due to a shortage of field data, which are spatially and temporally limited. As a result, simplifying assumptions are needed to model fuel loading over larger areas to compensate for this shortage of data. Assumptions include the ecological relationship between canopy and understory fuels, or the common method of cross-walking vegetation cover to fuel characteristics (Keane et al. 2001, Rollins and Frame 2006, Krasnow et al. 2009). Uncertainty can also occur due to limitations from remote sensing technology used to extrapolate from field data. Landsat, for example, has difficulty in estimating understory fuel conditions under forest canopies or areas with high tree density (Arroyo et al. 2008, Jakubowksi et al. 2013), or in sites that differ in vegetation height or understory composition (Riaño et al. 2002). Additionally, regional-scale methodologies developed in locations with an abundance of underlying field data may not accurately predict fuel conditions in other regions with different fuel dynamics (Rollins and Frame 2006). Lack of precision is further exacerbated in landscapes comprised of spatially and temporally variable vegetation types, such as invaded tropical grasslands (Ellsworth et al. 2013), or in areas where topography contributes to high climatic and ecological variability across small distances, such as the case in the Hawaiian Islands. Therefore, evaluating and improving the quality of fuel mapping for wildfire management requires understanding and addressing these limitations.

Study overview

The first study in this thesis is titled '*Moisture availability regulates increases in fine fuels and modeled wildfire behavior following nonnative feral ungulate removal in Hawaii.*' The concept for the chapter was developed in response to a persistent question among scientists and land managers in Hawaii over what impacts the removal of nonnative feral ungulates from a site has on the build-up of fuels. The common assumption was that ungulate removal, absent any additional active management to reduce fuels, would result in substantial build-up of fuels that would create significant wildfire risks. Noting a lack of research to back up such assumptions, I devised a study to determine what relationships exist between the removal of ungulates, the build-up of fuels, and other management, site, and climatic factors. Past research focused on the impacts of ungulate removal on non-fuels-related characteristics of ecosystem recovery, or on the impacts of domestic grazing and exclusion on fuels. To my knowledge, there has been no systematic study of the impacts of nonnative feral ungulate exclusion on fuels and wildfire behavior, particularly across a wide precipitation gradient or on a tropical Pacific Island. To address this knowledge gap, I developed three main research objectives: (*i*) determine the effect of nonnative feral ungulate removal on fuels characteristics and modeled wildfire behavior; (*ii*) determine how the effects of nonnative feral ungulate removal vary with moisture availability; and (*iii*) determine the impacts of ecological restoration on fuel characteristics and modeled wildfire behavior after nonnative feral ungulate removal. To address these research objectives, I analyzed differences in fuel characteristics and modeled wildfire behavior inside and outside of a series of ungulate exclosures located across a 2740 mm mean annual precipitation gradient on the Island of Hawaii.

The second study, titled '*Random Forest fuel mapping across a heterogeneous dry tropical montane landscape,'* addresses another pressing issue in assessing the accuracy of standard surface fuel maps in Hawaii. Fuel mapping is highly uncertain in Hawaii and the tropical Pacific Islands, largely due to a shortage of field measurements and validation of existing fuel maps, as well as landscapes composed of spatially and temporally variable vegetation types, novel fuel beds, invasive species, and high climatic and ecological variability over small distances. To address this uncertainty, I compared the accuracies in fuel model assignments of the standard LANDFIRE surface fuel map with a custom fuel map that used a mixed methods approach combining field sampled fuel data, biophysical predictors, and Random Forest classification in a highly heterogeneous, tropical dry montane landscape. To my knowledge, this is the first landscape-scale evaluation of LANDFIRE fuel mapping accuracy in Hawaii.

Chapter 2: Moisture availability regulates increases in fine fuels and modeled wildfire behavior following nonnative feral ungulate removal in Hawaii

Abstract

The removal and exclusion of nonnative feral ungulates for conservation of biodiversity is widespread on tropical Pacific Islands. However, the effects of ungulate exclusion on fuels and wildfire have not been systematically studied. I sampled fuels (live and dead fuel loads, type, height, and continuity) and modeled potential wildfire behavior (flame height and rate of spread) inside and outside of 13 ungulate exclosures, including three exclosures with additional ecological restoration (e.g., outplanting of native species), across a 2740 mm mean annual precipitation (MAP) gradient on the Island of Hawaii. I then assessed differences in fuel characteristics and modeled wildfire behavior inside vs. outside of ungulate exclosures using linear mixed effects analyses. Nonnative feral ungulate removal increased fine fuel loading (average differences ranged from -0.7 to 11.3 Mg ha^{-1}), shrub fuel loading (-0.1 to 5.6 Mg ha^{-1}), and modeled flame lengths (-0.2 to 1.9 m). Moreover, fine fuel loading and modeled flame lengths increased linearly and positively with moisture availability. Sites undergoing ecological restoration exhibited reduced fine fuel loading, with reductions increasing with time since ungulate removal. By the tenth year after ungulate removal, fine fuel loading was reduced at restoration sites by 41% (an average of 5.1 Mg ha^{-1}). Dry and mesic environments where wildfire occurrence is more frequent are of particular concern following nonnative feral ungulate removal, but with drought even typically wet environments can be at high risk of wildfire. My results demonstrate a clear trend in increased fuel loads after ungulate removal across a wide precipitation gradient, and point towards the need for effective fuels management strategies, such as long-term active ecological restoration, to reduce fuel loads and invasive species cover so as to break the positive feedback between nonnative invasions and wildfires.

Keywords: Ecological restoration, nonnative grass-fire cycle, Pacific Island Region, mean annual precipitation gradient, ungulate removal, wildfire management

Introduction

Global wildfire activity poses a significant risk to human health and safety (Bowman et al. 2017), biodiversity (D'Antonio and Vitousek 1992), watershed conservation (Sankey et al. 2017, Trauernicht et al. 2018), primary productivity (Hawbaker et al. 2017), and other ecosystem goods and services (Moritz et al. 2014). Native ecosystems globally are increasingly challenged by novel wildfire regimes driven by both nonnative species invasion and landscape-scale disturbances (Hughes et al. 1991, Litton et al. 2006, Krawchuk et al. 2009, Jolly et al. 2015). The contemporary wildfire regime in Hawaii, for example, is characterized by a substantial increase in the extent of area burned over the past 100 years, much of it driven by the widespread invasion of fire-prone and fire-adapted nonnative grasses and shrubs (D'Antonio and Vitousek 1992, Trauernicht et al. 2015). Despite increased investments in wildfire management (e.g., fuel reduction treatments and public outreach/education), mitigating wildfire risk and identifying better methods for allocating limited fuels management resources remains a significant challenge (Stephens and Ruth 2005). The most typical means of reducing wildfire hazard and severity in the continental United States is through the manipulation and reduction of wildland fuels, or the dead and live biomass available for fire ignition and combustion (Keane et al. 2001), which is commonly accomplished via mechanical thinning or prescribed fire (Fule et al. 2001, Pollet and Omi 2002, Stephens et al. 2009). The wildfire landscape of Hawaii is complicated, however, by novel fuel beds and the presence of numerous introduced nonnative feral ungulate species that likely have important, but largely unknown, consequences for fuels management (Chynoweth et al. 2013, Hess 2016, Wehr et al. 2018).

Domesticated cattle (*Bos taurus*), goats (*Capra hircus*), sheep (*Ovis aries*), axis deer (*Axis axis*), and Polynesian, domestic, and wild European pig varieties (*Sus scrofa*) have been introduced to Hawaii over the course of prior centuries, and have established widespread feral populations throughout Hawaii, in addition to many other Pacific Islands (Hess 2016). These invasions cause substantial ecological degradation through the direct effects of herbivory, browsing, trampling, and bark stripping, as well as indirect effects via alterations in ecosystem processes such as hydrology and nutrient cycling (Cole and Litton 2014, Long et al. 2017, Wehr et al. 2018). From a wildfire standpoint, these invasions can reduce fine fuel loads and increase the discontinuity of the fuel bed (Kellner et al. 2011), with important implications for the occurrence and spread of wildfires. The presence of introduced feral water buffalo in Northern Australian savannas, for example, has been observed to reduce wildfire probability (Trauernicht et al. 2013). Although nonnative feral ungulates are considered incompatible with native species conservation in Hawaii and throughout the Pacific Island region, carefully targeted and managed ungulate grazing is a potentially beneficial strategy, with demonstrated success in reducing fuel loads and modeled wildfire behavior, at least over the short-term (Blackmore and Vitousek 2000, Leonard et al. 2010, Evans et al. 2015).

In response to the widespread negative impacts of introduced ungulates, fencing and removal of nonnative feral ungulates is an increasingly common management strategy for conserving and restoring native biodiversity (Zavaleta et al. 2001, Cole and Litton 2014, Hess 2016). Over the past 30 years, management agencies in Hawaii have fenced and removed nonnative feral ungulates from >750 km^2 of public land (Hess 2016). These efforts have been highly effective at reducing ungulate densities within management units, with important conservation benefits in most cases. However, at many sites ranging from dry to wet environments, nonnative feral ungulate removal can increase the cover of both native and nonnative plants due to release from top-down control, especially at sites with a substantial nonnative plant presence at the time of ungulate removal (Stone et al. 1992, Cabin et al. 2000, Kellner et al. 2011, Cole et al. 2012).

The degree to which ungulate removal impacts wildland fuels and wildfire behavior remains largely unquantified, especially on tropical Pacific Islands. Wildfire and herbivores are competing “alternative consumers” of vegetation (Bond and Keeley 2005), and similar to wildfire, the magnitude and direction of the effects of ungulate removal effects may depend on moisture availability. For example, an Australian study of managed grasslands found that five to ten years after removing grazing herbivores, including deer, kangaroos, rabbits, and sheep, phytomass increased by an average of 737%, and mean annual precipitation (MAP) accounted for 42% of the observed variation in phytomass accumulation (Schultz et al. 2011). In contrast, Koppel et al. (1996) documented that in systems of high productivity in the Netherlands, grazing pressure did not keep pace with plant growth, such that there was little difference in phytomass in the presence of herbivores. Moreover, Leonard et al. (2010) found that low moisture at grazing sites hindered the ability of grasslands to accumulate fuel under even relatively low grazing pressure.

A potential mechanism to reduce fuels following ungulate removal lies in ecological restoration (e.g., outplanting of native species, nonnative plant control). Active ecological restoration after the fencing and removal of ungulates is a common approach at degraded sites (Banko et al. 2014). However, little is known about how this practice affects fuel loads or the potential for wildfire. At degraded sites, fencing without active ecological restoration can result in a substantial increase in nonnative species that interferes with the regeneration of native species, as has been shown in dry and mesic systems in the Hawaiian Islands (Cabin et al. 2000, Weller et al. 2011). Such studies indicate that fencing without active ecological restoration is not enough to achieve the conservation objective of returning an ecosystem to a native reference ecosystem. In turn, active ecological restoration has been shown to be useful for reducing fuel loads and wildfire risk. For example, Ellsworth et al. (2015) demonstrated in experimental trials in highly degraded sites in leeward Oahu, Hawaii that after 27 months of active restoration (i.e., native species outplanting and herbicide application on nonnative grasses), invasive grass fuel loads decreased by > 82%. Given high initial investment costs in restoration projects (Powell et al. 2017, Wada et al. 2017), understanding the impact of ecological restoration after nonnative feral ungulate removal over longer time periods (e.g., > 5 years) is critical to informing management decisions.

The primary objectives of this study were to: (*i*) determine the effect of nonnative feral ungulate removal on live and dead fuel loads, type, height, and modeled wildfire behavior; (*ii*) determine how the effects of ungulate removal vary with moisture availability; and (*iii*) determine the impacts of ecological restoration on fuel characteristics and modeled wildfire behavior after ungulate removal. I hypothesized that: (*H1*) removal of ungulates would increase fuel loads and modeled wildfire behavior, including flame height and rate of spread (Blackmore and Vitousek 2000, Schultz et al. 2011, Evans et al. 2015); (*H2*) the magnitude of changes in fuel characteristics and modeled wildfire behavior with ungulate removal would be driven by moisture availability, where ecosystems with very low (< 800 mm yr^{-1}) or very high (>2000 mm yr^{-1}) precipitation would show little difference in fuel loads and wildfire behavior following ungulate removal, while in mesic ecosystems with intermediate levels of precipitation (800-2000 mm yr^{-1}) ungulate removal would increase fuels and modeled wildfire behavior (Murphy et al. 2011, Pausas and Ribeiro 2013); and (*H3*) ecological restoration in sites that have experienced ungulate removal would reduce fuel loads and modeled wildfire behavior (Ellsworth et al. 2015). To address these hypotheses, I analyzed differences in fuel characteristics and modeled wildfire behavior inside and outside of a series of ungulate exclosures located across a 2740 mm mean annual precipitation gradient on the Island of Hawaii.

Methods

Study Area

This study was conducted across 13 sites spanning a 2740 mm mean annual precipitation (MAP) gradient (460 to 3200 mm yr^{-1}) on the Island of Hawaii, with field sampling occurring from June 2016 to June 2017 (Table 1 and Figure 1). Mean annual precipitation values were obtained from the Online Rainfall Atlas of Hawaiʻi (Giambelluca et al. 2013). To better capture MAP effects on fuels and wildfire with ungulate removal, I utilized moisture zone classifications developed for the Hawaiian Islands by Price et al. (2012a). Moisture zones offer a more useful approach than MAP by modeling moisture availability as a function of annual precipitation, potential evapotranspiration, trade wind exposure, and elevation. Study sites ranged from moisture zone 2 to 6, and were classified as very dry (2), moderately dry (3), seasonally mesic (4), or moderately wet (6) (Table 1).

Sites ranged in elevation from 259 to 2359 m asl. Mean annual temperature (MAT) ranged across sites from 9 to 22 °C (Giambelluca et al. 2013). Land cover varied from grassland to shrubland to forest, with invasion status ranging from native-dominated to mixed to invasive-dominated. At sites where there was a substantial canopy, native trees were most common, while nonnative grasses dominated the understory. Sampled exclosures were 4 to 15 years of age with respect to time since ungulate removal. Ownership of study sites included state land managed under several different agencies, private land managed by non-profit organizations, and federally owned and managed land. Ungulates present in the study sites included feral cattle, feral goats, feral sheep, feral pigs, and various combinations of these species (Table 1). For the purposes of understanding the impacts of unmanaged nonnative feral ungulates, sites were chosen based on the presence of feral ungulates and the absence of domestic, managed ungulates.

Study sites were located with the assistance of land managers and expert opinion, and each of the 13 sites consisted of paired plots with three 50 m sampling transects located both inside and outside of each ungulate exclosure. Each paired plot was ≤70 meters away from each other and ≥30 meters from the fence line. Within a given site, plots on either side of the fence were established based on similarity in vegetation type, forest canopy cover, proximity, management and disturbance histories, and environmental attributes (i.e., MAP, MAT, moisture zone, elevation, aspect, slope, and soils). Three additional removal units, which differed in time since ungulate removal from four to ten years, were sampled at a single seasonally mesic site to explore if active ecological restoration (i.e., outplanting of native trees and shrubs, and invasive grass control around individual outplants during the initial stages of planting) altered the impact of ungulate removal on fuel loads and wildfire behavior.

Fuel Characteristics

Three 50 m transects separated by 20 m were established inside and outside of each exclosure to sample fuel loads, fuel moistures, and fuel height. The initial transect for each plot was established parallel to the fence line with each subsequent transect placed 20 m from the first transect. Several fenced plots were compared with a single unfenced plot. Specifically, paired plots labeled as MA, MU, and PA, and 4CNW, 4CSE, and 4CSW were adjacent fenced plots that were compared with a single adjacent unfenced control (Table 1).

Fine fuel loads were measured by collecting all litter (i.e., leaves, downed grass and herbaceous biomass, and woody material <1 cm diameter) to the mineral soil surface, and clipping standing grass and herbs down to the soil surface in six 25 x 25 cm subplots along each transect (0, 10, 20, 30, 40, and 50 m). Samples were returned to the lab within 48 hours, sorted by species into live and dead biomass, oven dried at 70°C to a constant mass, and weighed to determine fine dry fuel mass. The height of the tallest plant was measured in each subplot prior to collection, and fuel bed depth was calculated as 70% of the measured maximum fuel height (Burgan and Rothermel 1984). Coarse woody fuels (> 1 cm diameter) were measured using a modified Brown's fuel transect following National Park Service standard protocols (NPS 2003). A two-meter-wide belt transect was established along each 50 m transect to quantify standing woody fuels (i.e., shrubs and trees), where shrub basal diameter and tree diameter at breast height were measured to estimate woody fuel loads with species-specific allometric models developed in Hawaii (Litton and Kauffman 2008, Ammondt et al. 2013), or generalized allometry when species-specific data were not available (Chave et al. 2005). Plant cover was quantified by recording species, litter, or bare substrate cover types every 1 m along each 50 m transect using a modified point-intercept method for the understory and a densiometer for the overhead canopy,.

Wildfire Behavior Modeling

Potential wildfire behavior was modeled using the BehavePlus 5.0.5 modeling system (Heinsch and Andrews 2010) and data on fuel characteristics collected in this study. Additional required parameters were obtained from relevant literature, including 1-hr surface area:volume, dead fuel moisture of extinction, and live and dead fuel heat content (Scott and Burgan 2005). To isolate the effect of ungulate removal on wildfire behavior and assess its relationship with site average moisture availability, weather (e.g., wind speed) and terrain variables (e.g., slope) were kept constant at standard BehavePlus settings in all simulations. Model output variables included maximum rate of spread (m min^{-1}) and flame length (m), both indices of wildfire intensity.

Statistical Analysis

To test my hypotheses, I compared fuel characteristics (live and dead fuel loading, type, height, and continuity) and modeled BehavePlus outputs (flame height and rate of spread) in unfenced ungulate present (U) vs. fenced ungulate removal (F) sites. To understand the effect of moisture availability, I analyzed differences in fuel characteristics and modeled wildfire behavior between paired U and F plots along the precipitation gradient using a linear mixed effects analysis. Due to the observational and non-parametric nature of many field ecology datasets, Adams et al. (1997) suggested that mixed effects analyses can be more appropriate for ecological studies where variables are difficult to control. I used R (Team 2017) and the "nlme" package (Pinheiro et al. 2017) to perform a linear mixed effects analysis of the relationship between potential explanatory variables and response variables at the subplot level (n = 359). Fixed effects were MAP, MAT, moisture zone, years since ungulate removal, and fencing treatment (i.e., U vs. F). Site was a random effect to account for the potential lack of independence due to the paired plot design of the study. Response variables were transformed where necessary to meet assumptions of homogeneity of variance.

Models (n = 44) were built containing combinations of all variables, including a "null" model that contained no fixed effects and only site as a random effect. Through multi-model inference, Akaike's information criterion (AIC) was used to select the best model from multiple competing models by using a comparison of Akaike weights (w_i; the conditional probability that a given model is the most informative and parsimonious of those considered) and Δ_i (the difference between the AIC value of the best model and the next model under consideration)(Burnham 2002). Models with $w_i > 0.90$ and $\Delta_i < 2$ were considered to have substantial empirical support per Symonds and Moussalli (2011). The impact of ungulate removal on fuels in ecological restoration sites was tested with analysis of variance (ANOVA), with Tukey's Honest Significant Differences test used to test for differences in plot-level (i.e., treatment) means following significant ANOVAs. Testing the impact of ungulate removal on wildfire behavior in restoration sites was not possible due to limited sample size. All analyses were conducted at a significance level of $\alpha = 0.05$.

Results

Fuel Characteristics

Total fine fuel loads ranged widely across all fenced and unfenced plots from 0.1 to 18.0 Mg ha^{-1} (Table 1). By moisture zone, total fine fuel loads averaged 2.9 Mg ha^{-1} in the very dry moisture zone, 5.6 Mg ha^{-1} in the moderately dry moisture zone, 10.2 Mg ha^{-1} in the seasonal mesic moisture zone, and 12.5 Mg ha^{-1} in the moderately wet moisture zone (Table 1). Fine fuel loading averaged 6.6 Mg ha^{-1} in fenced plots and 4.4 Mg ha^{-1} in unfenced plots. Fine fuel load differences between paired plots averaged 2.6 Mg ha^{-1} with ungulate removal and ranged from 0.2 to 11.3 Mg ha^{-1}, which represented an average increase of 46% with ungulate removal (Table 1). Fine fuel height averaged 0.79 m in fenced plots and 0.68 m in unfenced plots, and fine fuel height differences between paired plots averaged 0.10 m and ranged from -0.10 m to 0.28 m.

Moisture zone, fencing treatment, and their interaction were the best predictors of fine fuel loading (w_i = 0.91), indicating that moisture availability and ungulate removal both increase fine fuel loading, with the magnitude of ungulate removal impacts on fine fuel loading increasing with moisture zone (Figure 2). The next closest performing model (w_i = 0.05) also included MAT as an explanatory variable, but this model had a low Akaike weight and high Δ_i and was not considered to have substantial empirical support. The null model performed poorly as well (w_i < 0.01). Fuel height was best predicted by fencing treatment, MAT, moisture zone, the interaction between moisture zone and fencing treatment, and years since ungulate removal (w_i = 0.48). A model (Δ_i < 2) that additionally excluded MAT as a predictor also had some empirical support (w_i = 0.18).

Sites with shrubs as a major component of fuel loading were clustered on the very dry to moderately dry moisture zones (i.e., <800 mm yr^{-1}), with shrubs absent in higher moisture zones. Shrub fuel loading across paired plots averaged 0.3 to 2.1 Mg ha^{-1}. Shrub fuel loading differences between paired plots averaged 0.8 Mg ha^{-1} with ungulate removal (Figure 3). Shrub fuel loading was best predicted by fencing treatment alone (w_i = 0.34). Models with Δ_i < 2 that included years since removal (w_i = 0.20) and years since removal and moisture zone (w_i = 0.15), in addition to fencing treatment, as predictors also had substantial empirical support.

Live fine fuel loads averaged 6.8 Mg ha^{-1} in fenced plots and 5.7 Mg ha^{-1} in unfenced plots. Dead fine fuel loads averaged 3.2 Mg ha^{-1} in fenced plots and 1.7 Mg ha^{-1} in unfenced plots. Live fine fuel loading was best predicted by MAT, moisture zone, fencing treatment, and the interaction between fencing treatment and moisture zone (w_i = 0.42). Dead fine fuel loading was best predicted by fencing treatment, moisture zone, the interaction between fencing treatment and moisture zone, and years since removal (Figure 4, w_i = 0.75). The ratio of dead fuel to total fuel ranged from 0.0 to 0.78 in fenced plots, and 0.0 to 0.86 in unfenced plots, with differences between unfenced and fenced paired plots ranging from 0.0 to 0.59.

Vegetation cover at sites tended to be dominated by nonnative grasses, but at times had substantial cover as bare ground and native shrubs and trees. For all classes of vegetation cover except grass, the null model performed best. Grass cover, in turn, was best predicted by moisture zone alone (w_i = 0.89). Fuel continuity (vegetation cover vs. bare ground) was best predicted by the null model.

Fine fuel loads in ecological restoration plots ranged from 14.6 Mg ha^{-1} four years after ungulate removal to 7.3 Mg ha^{-1} ten years after ungulate removal, compared to the unfenced plot which averaged 12.4 Mg ha^{-1} (Table 1). A model (w_i = 0.99) that included years since removal and fencing treatment as factors performed best in predicting fine fuel loading in restoration plots, indicating that fine fuel loading generally decreased after fencing treatment and as the number of years after ungulate removal increased. While fine fuel loads remained relatively constant four years after fencing, by year six fuel loads in fenced units with ecological restoration had decreased below the level of the unfenced control, and by the tenth year after ungulate removal, fine fuel loading was reduced by 41% compared to the control (an average of 5.1 Mg ha^{-1}) (Figure 5).

Wildfire Behavior Modeling

Modeled flame length ranged from 0.5 to 5.4 m height, and absolute differences in flame length between fenced and unfenced paired plots ranged from 0 to 1.9 m. In line with fine fuel loading, flame length was best predicted by moisture zone, fencing treatment and their interaction, indicating that flame length (i.e., fire intensity) increases with ungulate removal and that the impact of ungulate removal increases in magnitude with increasing moisture zone (Figure 6, w_i = 0.907). Modeled rate of spread ranged from 1.3 to 57.1 m min^{-1}, and absolute differences in rate of spread between fenced and unfenced paired plots ranged from 0.3 to 2.4 m min^{-1}. Rate of spread was best supported by the null model. At restoration sites, modeled flame length ranged from 2.7 m ten years after ungulate removal to 3.7m in the unfenced plot, and rate of spread ranged from 9.6 m min^{-1} ten years after ungulate removal to 11.2 m min^{-1} in the unfenced control plot.

Discussion

The proper management of wildfire in the context of invasive plant and animal species is crucial to the conservation and restoration of threatened landscapes in the Pacific Island Region, and throughout the world. Results from this study show that nonnative feral ungulate removal increased fine fuel loading, shrub fuel loading, and modeled wildfire intensity (i.e., flame length), confirming my first hypothesis (H1). These results are consistent with prior research on managed grazing where domestic ungulates reduced fuel loads and potential wildfire behavior (Blackmore and Vitousek 2000, Leonard et al. 2010, Evans et al. 2015). Across study sites, nonnative feral ungulates likely reduced fuel loads by removing grass and herbaceous biomass through consumption, while also potentially altering fuel structure and continuity.

The effect of ungulate removal on fuel loads and modeled wildfire intensity increased linearly with moisture zone, which does not support my second hypothesis (*H2*) that the magnitude of changes in fuel characteristics and modeled wildfire behavior with ungulate removal would follow a unimodal relationship with moisture availability. Milchunas et al. (1988) suggested a generalized model for the effects of grazing by large herbivores on grasslands, where the magnitude of grazing effects are a function of productivity. This model was supported for the impacts of ungulate removal by Fernández-Lugo et al. (2013), who found that the effects of goat removal on species richness and composition in the Canary Islands were positively correlated with a productivity gradient. The results of this study demonstrate that the magnitude of fuel loading as a result of ungulate removal scales similarly on a moisture zone gradient. At the wettest sites, average fine fuel load differences ranged as high as 11.3 Mg ha^{-1}, representing a large increase in fuels with ungulate removal, while in the driest sites average fine fuel loads were reduced to as little as 0.2 Mg ha^{-1}. Leonard et al. (2010) observed that at sites with low moisture availability, only relatively low levels of grazing were required to maintain grasslands in a lawn-like state, compared to sites with higher moisture availability that required more intensive grazing, in line with my results for drier sites. In turn, removal of ungulates in wetter sites eliminates a primary consumer of fine fuels, creating an alternative demand for the consumption of this fuel in the form of fire (Bond and Keeley 2005).

Ungulate removal resulted in a modest increase in dead fine fuels, the more flammable portion of the total fuel loading that is a primary driver of grassland fire (D'Antonio and Vitousek 1992), although this effect was not significant. Because a sufficient amount of dead fuel is required to carry wildfire, sites that experience a subsequent build-up of dead fine fuels after ungulate removal will be at a greater risk for fire. The modest increase in dead fine fuel loads align with past observations, where the absence of ungulates in grasslands resulted in increases in dead fine fuel (Leonard et al. 2010). Ungulates likely prevent the accumulation of dead fine fuels through herbivory and trampling (Morgan and Lunt 1999, Whalley 2005). Similarly, Evans et al. (2015) observed that targeted, managed grazing by high density domestic ungulates resulted in a reduction in dead fine fuels relative to live fine fuels.

The combination of nonnative feral ungulate removal and ecological restoration reduced fine fuel loads and modeled wildfire behavior, with this reduction increasing with time since nonnative feral ungulate removal, confirming my third hypothesis (*H3*). While sampling of restoration sites was limited to three fenced units in the same moisture zone, these results suggest that ecological restoration can effectively suppress the growth of fuels (e.g., nonnative grasses) that occurs with ungulate removal, and offers evidence of the longer-term utility of shading and reduction of fine fuels using ecological restoration (Cabin et al. 2002, Ammondt and Litton 2012, Medeiros et al. 2014, Ellsworth et al. 2015). At six years after ungulate removal and active restoration, fuel loads had decreased significantly, and by the tenth year after ungulate removal, fine fuel loads had decreased by nearly half. Ecological restoration at these sites consisted primarily of outplanting native trees and shrubs, offering additional evidence for the effectiveness of native species outplanting for reducing fuel loading when compare to just using herbicide (Ellsworth et al. 2015). Though the observed reduction in fuels with ungulate removal and active ecological restoration is likely dependent on the initial degradation of a site and the intensity of ecological restoration (Weller et al. 2011), my results suggest that significant decreases in fuel loading from ecological restoration are achievable, particularly over longer time scales.

Because the sampling method used in the study was opportunistic in that it took advantage of available fenced exclosures, it is possible that other factors may affect fuel characteristics in ways not captured in this study. These potential factors include vegetation palatability, foraging habits of different types of ungulates, seasonal controls on ungulate migration patterns, variations in ungulate densities, and prior level of degradation (Noy-Meir 1975, Hobbs 1996, Murphy and Bowman 2007). Moreover, the majority of the sampling for this study took place during the summer of a single year, with limited additional sampling in the summer of the second year. Significant variability may exist in fuel loading generally, as well as between fenced and unfenced units, due to seasonal differences or in response to extreme weather events (Ellsworth et al. 2013, Abatzoglou et al. 2018, Trauernicht 2019). Data obtained from Remote Automated Weather Stations closest to sampled sites show average precipitation from the preceding year (August 2015 to July 2016) ranged from 65% to 131% of long-term site MAP.

Land managers seeking to balance conservation and restoration objectives with wildfire risk need to be cognizant of the impacts of nonnative feral ungulate removal on fuels and wildfire behavior. At almost all sites examined, ungulate removal led to an increase in fuel loads and modeled wildfire behavior, even only a few years after exclusion. Dry and mesic moisture zones, in general, are of particular concern because wildfire occurrence is more frequent in these zones, but in drought years even wet zones are at risk for wildfire (Chu et al. 2002, Frazier 2016). For example, study sites on the wettest end of the precipitation gradient (~3200 mm yr^{-1}) experienced a period of extreme drought, prolonged periods of severe drought, and multiple periods of moderate drought between 2000 and 2019 (Svoboda et al. 2002). Furthermore, nonnative grasslands in Hawaii have demonstrated high intensity wildfire behavior in what would be considered benign weather conditions in the continental United States, such as high relative humidity and low wind (Trauernicht et al. 2015).

Shifting climate envelopes may also impact the susceptibility of sites to wildfire. Recent models of climate change in Hawaii predict that mesic zones will decrease in cover, with a subsequent increase in dry and wet zones (Selmants et al. 2017), which could shift peak wildfire risk to higher elevations with higher fuel loads (Trauernicht 2019). Climatic projections by Abatzoglou et al. (2018) of increased fuel aridity by mid-century will also potentially increase burned area, particularly in wet forests. As a result, increased fuel loading after ungulate removal in wet moisture zones may entail an even greater wildfire risk in the future.

Decisions made regarding ungulate removal and wildfire mitigation actions will need to rely at least in part on site-specific factors, but my results demonstrate clear, general trends in fuel loading after ungulate removal across a wide precipitation gradient. Mowing, thinning, green strips, managed grazing, and prescribed fire are among a number of potential fuels management strategies available for land managers to reduce fuel loads after ungulate removal (Trauernicht et al. 2015). In the long-term, active ecological restoration will also be necessary to reduce fuel loads as well as invasive species cover so as to break the positive feedback between nonnative invasions and wildfires.

Table 1. Summary of mean fine fuel loading (+/- 1 S.D.) in paired fenced and unfenced plots, with site mean annual precipitation (MAP), moisture zone, nonnative feral ungulates present, and years since ungulate removal.

Paired Plot	Fenced Fine Fuel Loading (Mg ha^{-1})	Unfenced Fine Fuel Loading (Mg ha^{-1})	MAP (mm yr^{-1})	Moisture Zone	Ungulates	Years Since Removal
4CNW	1.3 (3.3)	0.07 (0.2)	460	2 (Very Dry)	Goats, Sheep	6
4CSE	3.3 (5.9)	0.07 (0.2)	460	2 (Very Dry)	Goats, Sheep	8
4CSW	0.3 (0.6)	0.07 (0.2)	460	2 (Very Dry)	Goats, Sheep	15
KK	4.1 (4.7)	2.9 (5.5)	524	2 (Very Dry)	Goats, Pigs, Sheep	10
PL	4.9 (5.5)	2.6 (2.3)	571	3 (Moderately Dry)	Cattle, Goats, Sheep	6
MA	14.6 (4.2)	12.4 (2.7)	686	4 (Seasonal Mesic)	Cattle, Pigs, Sheep	4
MU	7.3 (4.8)	12.4 (2.7)	686	4 (Seasonal Mesic)	Cattle, Pigs, Sheep	6
PA	11.3 (2.4)	12.4 (2.7)	686	4 (Seasonal Mesic)	Cattle, Pigs, Sheep	10
PN	7.7 (6)	4.6 (5.2)	782	3 (Moderately Dry)	Goats, Sheep	5
KC	7.3 (2.5)	5.2 (4.7)	1300	3 (Moderately Dry)	Cattle, Pigs, Sheep	9
KL	9.3 (3.7)	6.5 (2.8)	1700	4 (Seasonal Mesic)	Cattle, Pigs, Sheep	9
KA	15.1 (4)	6.6 (3.9)	3200	6 (Moderately Wet)	Cattle	4
KO	18 (3.5)	11.4 (3.9)	3200	6 (Moderately Wet)	Cattle	8

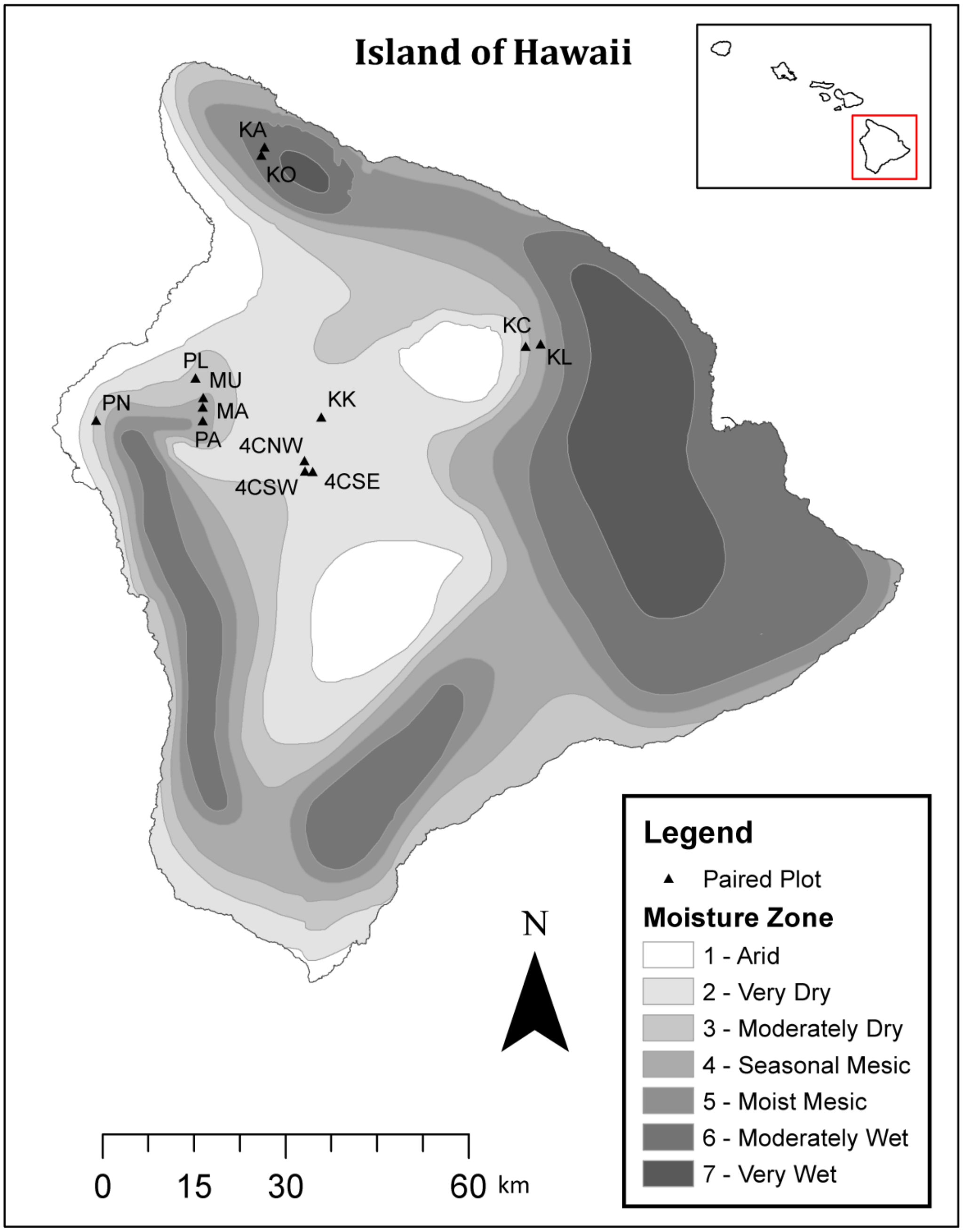

Figure 1. Paired fenced and unfenced plots by moisture zone on the Island of Hawaii, Hawaii. Paired plots were located in very dry (2), moderately dry (3), seasonal mesic (4), and moderately wet (6) moisture zones.

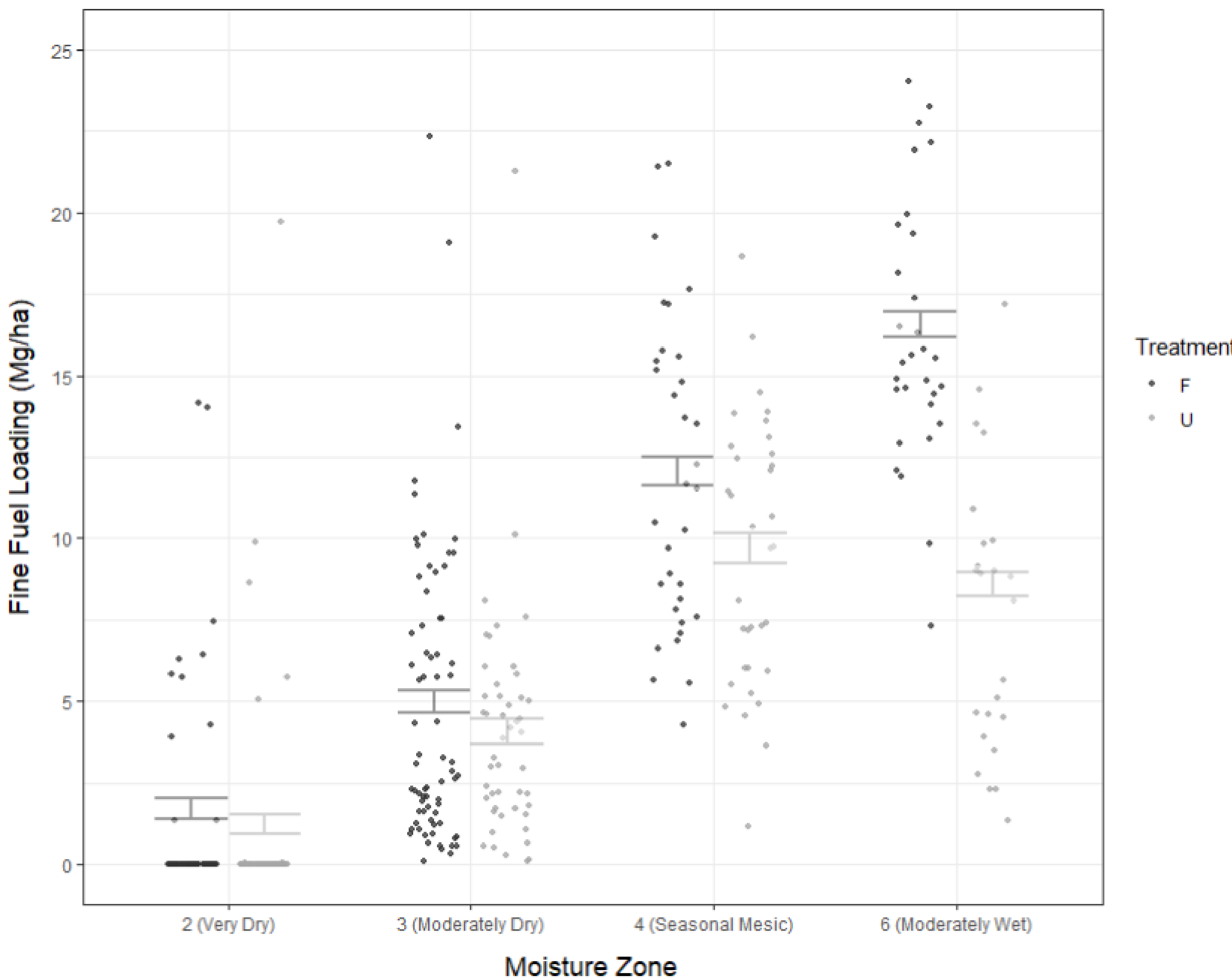

Figure 2. Fine fuel loading by fencing treatment (fenced (F) and unfenced (U)), as a function of moisture zone. Fine fuel loading includes live and dead standing grass and herbaceous fuels, as well as surface litter. Points represent sampled subplots (n = 359). Error bars indicate 95% confidence intervals of predicted model results.

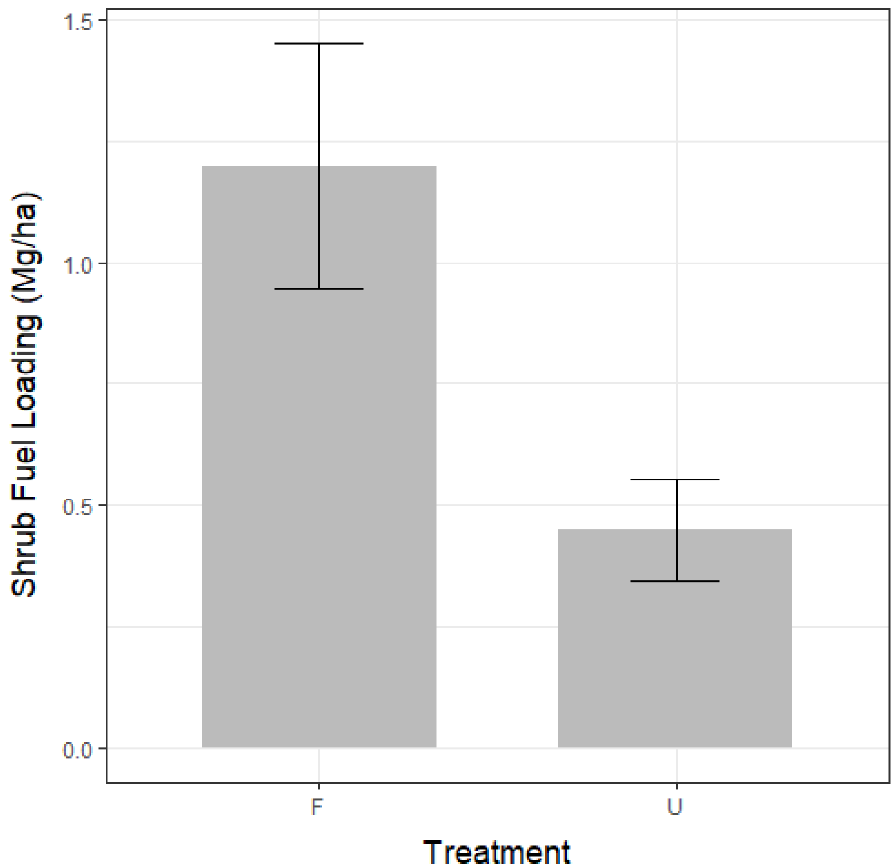

Figure 3. Mean shrub fuel loading (±1 SE) at all sites by fencing treatment (fenced (F) and unfenced (U)).

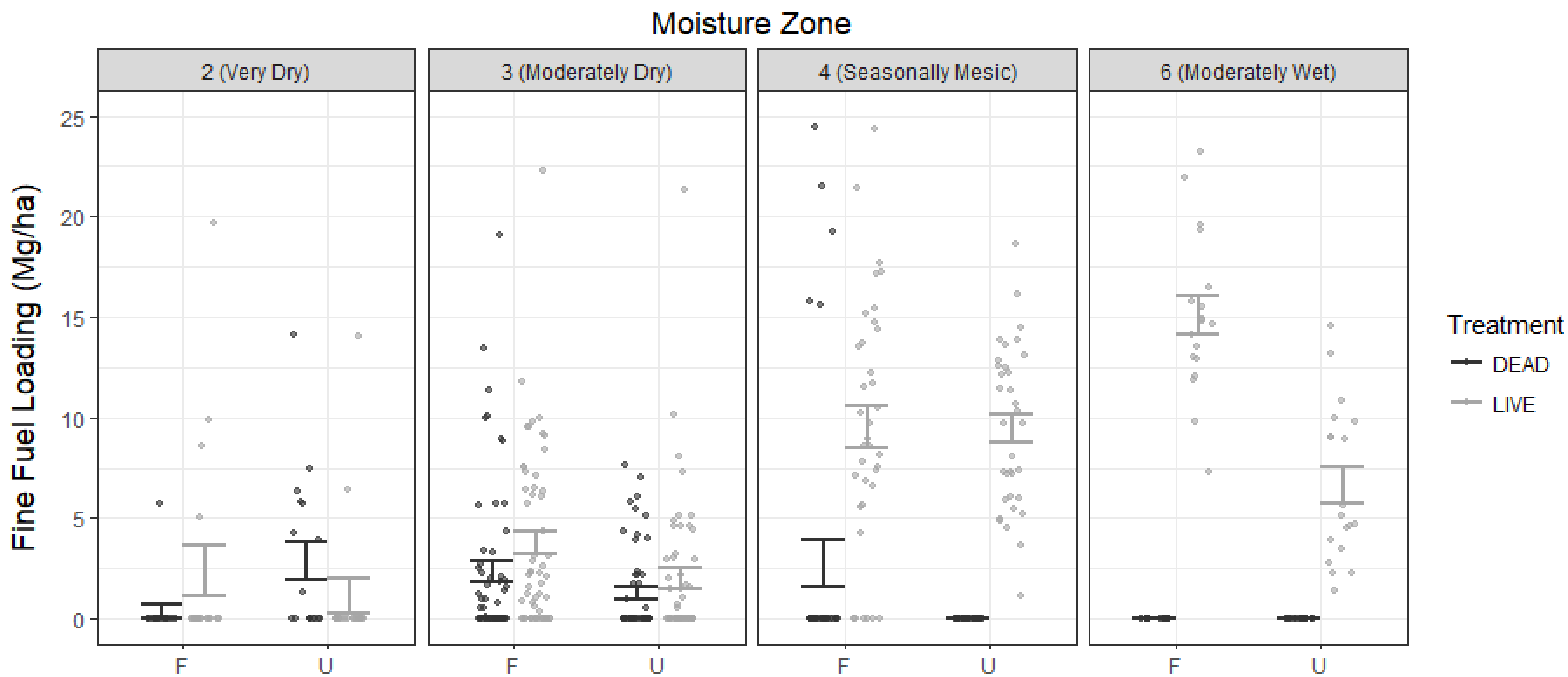

Figure 4. Sampled fine fuel loading by live and dead fuel components, moisture zone, and fencing treatment (fenced (F) and unfenced (U)). Fine fuel loading includes live and dead standing grass and herbaceous fuels, as well as surface litter. Points represent sampled subplots (n = 359), divided into separate subplots containing only live or dead fuels. Unfenced plots in moisture zone 4 and paired plots in moisture zone 6 did not have any dead fine fuel. Error bars indicate ±1 SE.

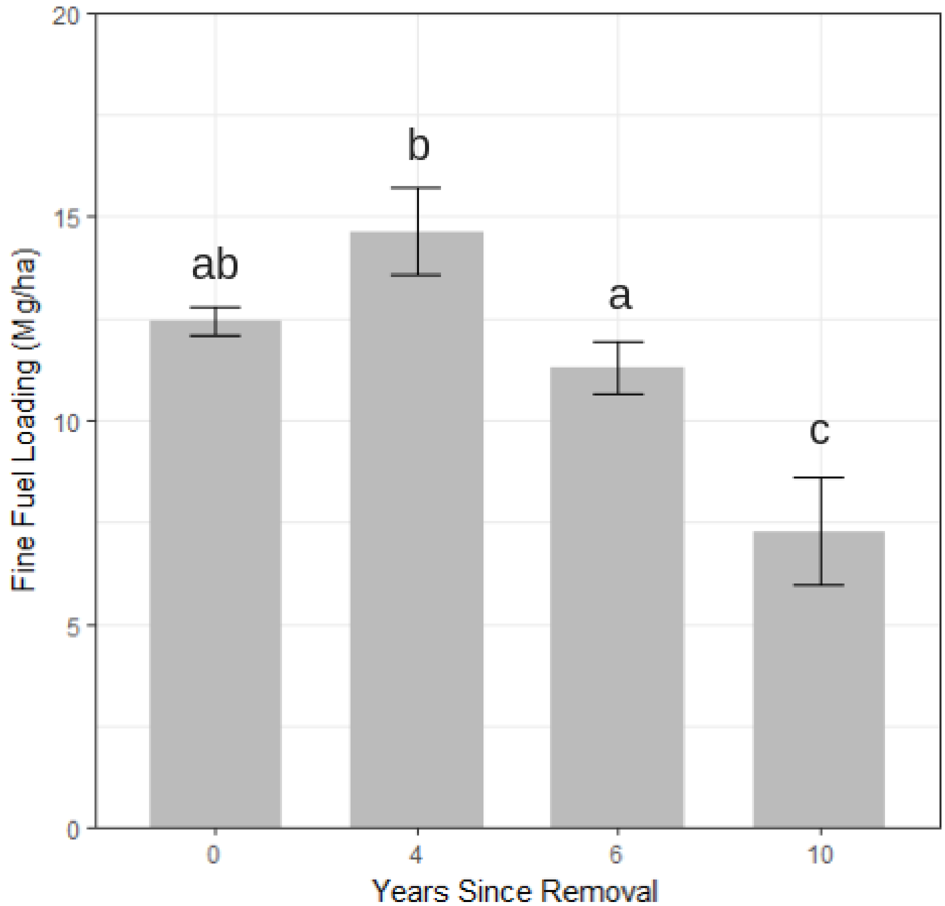

Figure 5. Sampled fine fuel loading differences in seasonally mesic restoration sites by years since ungulate removal. Error bars indicate ±1 SE. Lowercase letters designate plots that differ significantly in fine fuel loading. Significance was set at $p < 0.05$ and determined using ANOVA and Tukey's Honest Significant Differences.

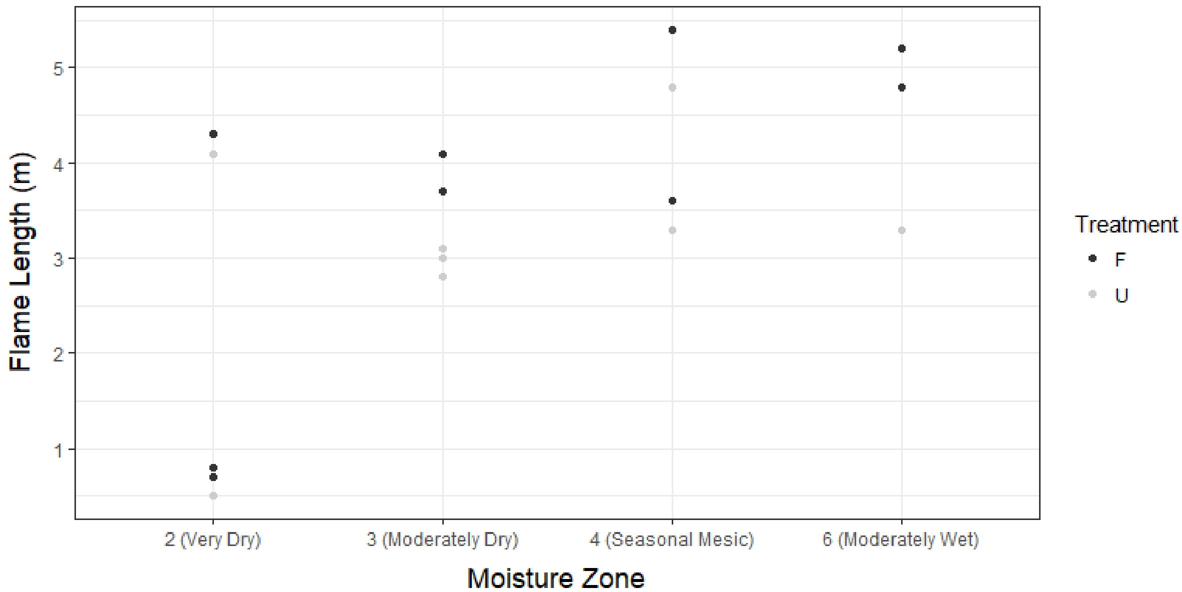

Figure 6. Modeled flame length by fencing treatment (fenced (F) and unfenced (U)) and moisture zone at all paired plots (with the exception of restoration sites). Modeled results are based on site-level averages.

Chapter 3: Random Forest fuel mapping across a heterogeneous dry tropical montane landscape

Abstract

Existing fuel maps for the Hawaiian Islands have largely not been validated, compromising efforts to make informed decisions about wildfire management. The Landscape Fire and Resource Management Planning Tools Program (LANDFIRE) provides regional-scale geospatial data on vegetation, wildland fuel, and wildfire regimes across the United States, including Hawaii. I sought to assess and compare the accuracy of fuels classification by LANDFIRE versus a custom mixed methods approach that combined field sampled fuel data, biophysical predictors, and remote sensing for a highly heterogeneous, tropical dry montane landscape encompassing multiple vegetation types with widely varying fuel characteristics. The custom fuel map approach involved: (*i*) assigning field sampled fuel data to fuel models based on a mathematical cluster classification, and (*ii*) combining cluster-derived fuel models with Landsat 8 imagery and biophysical predictors to create a landscape-level custom fuel map using Google Earth Engine and Random Forest classification. I then compared the custom fuel map and standard LANDFIRE fuel map for the study area by fuel model designations using confusion matrices and kappa scores. Total measured fuel loads were highly variable across vegetation types, ranging from 2.0 Mg ha^{-1} in *Styphelia-Dodonaea* shrubland to 23.4 Mg ha^{-1} in *Sophora* shrubland. The custom fuel map demonstrated a 58% accuracy with out-of-bag estimates. However, the cluster classification of sampled plots demonstrated only a 27% agreement with the standard LANDFIRE fuel model designations. Improvements in the custom fuel map over LANDFIRE included better discernment of fuel beds that lie on the threshold of being able to carry fire, and of plots with relatively high tree density. Variable importance plots showed normalized difference vegetation index, enhanced vegetation index, and Landsat bands 10, 11, and 6 as being important predictors for the custom fuel map. In line with previous research in temperate ecosystems, my analysis indicates LANDFIRE can provide a first approximation of fuel conditions and wildfire risk for understudied regions, but that supervised classification of local fuels data, biophysical predictors, and remote sensing can greatly improve accuracy and utility.

Keywords: cluster classification, fuel mapping, Google Earth Engine, LANDFIRE, Pacific Island Region, Random Forest, surface fuel models, wildfire management

Introduction

Making informed decisions on the management of wildfire-prone landscapes requires accurate and precise maps describing fuels, which are the dead and live biomass available for fire ignition and combustion (Keane et al. 2001). Accurate and precise mapping of fuel loads (biomass per unit area) and fuel structure that yields precise estimates can support efficient allocation of resources for fuel reduction treatments and informed wildfire suppression activities when fires do start. The scale of fuel mapping efforts range from local (Francesetti et al. 2006, Krasnow et al. 2009), to regional and continental (Rollins and Frame 2006), to global (Krawchuk et al. 2009). At the local scale of a wildfire management unit, fuel maps can be developed from intensive field-based collection of vegetation characteristics, with resulting fuel maps used to predict actual wildfire behavior (Pierce et al. 2012). Because detailed on-the-ground fuel mapping efforts are resource intensive and temporally limited (Krasnow et al. 2009, Pierce et al. 2012), larger-scale fuel mapping efforts frequently rely on hybrid approaches that include data from a variety of sources including vegetation plots in the field and high resolution remote sensing such as Landsat and LIDAR (Keane et al. 2001, Arroyo et al. 2008).

The most significant effort to project fuel characteristics across regional to continental scales is the Landscape Fire and Resource Management Planning Tools Program (LANDFIRE), which has developed baseline data on fuel characteristics for the entire United States (Rollins and Frame 2006), with repeat modeling used to assess trends at decadal time steps (Krawchuk et al. 2009). While this scaling approach was established by the United States Congress to provide baseline data for informing fire management across the United States, the accuracy of resultant large-scale mapping efforts are not well understood in under-sampled regions such as Hawaii, which uses LANDFIRE as its only baseline for landscape scale fuel assessment and modeling. One of the most widely used LANDFIRE products is the spatial assignment of the Scott and Burgan Fire Behavior Fuel Models (Scott and Burgan 2005), a set of surface fuel models that describe a particular area based on its dominant fire carrying fuel type. Fuel types are assigned to a particular model in the LANDFIRE product based on a combination of field data, image interpretation, remote sensing, and expert knowledge. The subjective nature of expert opinion and image interpretation can result in assignment errors and uncertainty that are largely unquantified, limiting the utility of LANDFIRE products, particularly at local scales. For example, Keane (2013) compared LANDFIRE spatial fuel products (Fuel Loading Models and Fuel Characteristic Classification System) with Forest Inventory and Analysis surface fuel estimates in the Western United States and found poor mapping accuracies primarily due to high variability in fuel loads within fuel model components that translated to inaccurate fuel model assignments. Krasnow et al. (2009) found that custom fuel maps produced through Classification and Regression Trees modeling of field plot data and local biophysical variables predicted the burned area of two historic fires more accurately than the corresponding LANDFIRE maps, primarily due to improved modeling of understory fuel components.

Uncertainty in fuel mapping can result from a lack of accuracy due to a shortage of field data, which are spatially and temporally limited. As a result, simplifying assumptions are needed to model fuel loading over larger areas to compensate for this shortage of data. Assumptions include the ecological relationship between canopy and understory fuels, or the common method of cross-walking vegetation cover to fuel characteristics (Keane et al.

2001, Rollins and Frame 2006, Krasnow et al. 2009). Uncertainty can also occur due to limitations from remote sensing technology used to extrapolate from field data. Landsat, for example, has difficulty in estimating understory fuel conditions under forest canopies or areas with high tree density (Arroyo et al. 2008, Jakubowksi et al. 2013), or in sites that differ in vegetation height or understory composition (Riaño et al. 2002). Additionally, regional-scale methodologies developed in locations with an abundance of underlying field data may not accurately predict fuel conditions in other regions with different fuel dynamics (Rollins and Frame 2006). Lack of precision is further exacerbated in landscapes comprised of spatially and temporally variable vegetation types, such as invaded tropical grasslands (Ellsworth et al. 2013), or in areas where topography contributes to high climatic and ecological variability across small distances, such as the case in the Hawaiian Islands. Therefore, evaluating and improving the quality of fuel mapping for wildfire management requires understanding and addressing these limitations.

My study addresses several important questions. How well does LANDFIRE represent fuels in Hawaii, and how does uncertainty vary with fuel type? Given limited fuel information, how can existing data and future fuel data collection be maximized? Can supervised classification methods combined with limited field sampling improve fuel mapping at the landscape level?

To address these questions, I compared and assessed the LANDFIRE surface fuel map for a highly heterogeneous dry tropical montane landscape in Hawaii with a custom surface fuel map created with Random Forest classification in Google Earth Engine that combined field data, Landsat reflectance data, and local biophysical data. Google Earth Engine (GEE) is a cloud-based remote sensing platform, which in combination with

Random Forest has proven effective in mapping woody vegetation clearing (Johansen et al. 2015), detecting industrial palm plantations (Lee et al. 2016), and modeling land cover dynamics at the regional scale (Huang et al. 2017). While other classification algorithms like Classification and Regression Trees have also been used to model fuels (Rollins and Frame 2006, Krasnow et al. 2009), Random Forest has seen increased use for fuel modeling due to its verified performance (Cutler et al. 2007, Pierce et al. 2012). My general approach to the custom fuel map involved: (*i*) assigning field sampled fuel data to fuel models based on a mathematical cluster classification; and, (*ii*) combining cluster-derived fuel models with Landsat 8 imagery and biophysical predictors to create a landscape-level custom fuel map that encompasses multiple vegetation types using Google Earth Engine and Random Forest classification. I then compared the custom fuel map and standard LANDFIRE fuel map for the study area by fuel model designations using confusion matrices and kappa scores.

Methods

Study Area

This study took place in the Pōhakuloa Training Area (PTA) of the United States Army Garrison Hawaii on the Island of Hawaii, which includes over 500 km^2 of highly diverse tropical dry montane landscape located on the saddle between Mauna Loa and Mauna Kea volcanoes. Elevation ranges from 1,250 m to 2,738 m. The area receives between 340 and 912 mm mean annual precipitation (Giambelluca et al. 2013), with all sampled plots located within a moisture zone classified as Very Dry by Price et al. (2012b). Average temperatures co-vary strongly with elevation, with average maximum temperatures ranging from 16.5 °C to 23.5 °C in July and average minimum temperatures ranging from 3.4 °C to 9.0 °C in January (Giambelluca et al. 2014). Frequent human-caused ignitions and infrequent lightning pose a substantial threat to PTA defense and environmental assets including human infrastructure multiple federally listed threatened and endangered species (Shaw and Castillo 1997).

Vegetation at PTA consists of tropical dry woodlands, shrublands, and grasslands. Twenty four major vegetation types were described and delimited by Shaw and Castillo (1997) and categorized by dominant canopy species and ground cover. Dominant vegetation types include the native trees *Metrosideros polymorpha* Gaudich (ʻōhiʻa), *Sophora chrysophylla* (Salisb.) Seem. (māmane), *Euphorbia olowaluana* Sherff (akoko), and *Myoporum sandwicensis* A. Gray (naio); native shrubs include *Dodonaea viscosa* (L.) Jacq. (ʻaʻaliʻi), *Styphelia tameiameiae* F. Muell. (pūkiawe), and *Chenopodium oahuense* (Meyen) Aellen (ʻāweoweo); and grasses include the native *Eragrostis atropioides* Hildebr. (lovegrass) and nonnative *Cenchrus setaceus* (Forssk) Morrone (fountain grass).

Geologically, PTA is complex and is underlain by many different aged ʻaʻa and pāhoehoe lava flows from both Mauna Loa and Mauna Kea (Sherrod et al. 2007). Soils at PTA are generally poorly developed. Barren lava flows account for over 20,000 ha of the ground surface. Andisols cover 13,097 ha of primarily Lithic, Humic, or Pachic Haplustands, while Histosols cover 11,440 ha of primarily Lithic Ustifolists.

Field Sampling and Fuel Model Assignment

Plots (n = 123) were located in a stratified random design across 20 of the 24 vegetation types defined in Shaw and Castillo (1997). The proportion of sample plots in each vegetation type matched the proportion of that vegetation type in the larger study area. Four vegetation types were excluded. Barren lava was excluded because it contains no vegetation or fuels, while the other three types (*Euphorbia olowaluana* woodland, dense *Dodonaea viscosa* shrubland, and *Styphelia tameiameiae* mixed shrubland) were excluded because they each occupy less than 60 ha total coverage. Plots were located within each vegetation type at an approximate density of 1 plot per 259 ha (1 mi^2).

In each plot, three 18.2 m fuel sampling transects were established along predetermined random azimuths. Each transect was sampled for 1-hr, 10-hr, 100-hr, 1000+-hr live woody and live herbaceous fuels, as well as duff depth, litter depth, and fuel bed height using the protocols described by Brown (1971). 1-hr and 10-hr fuels were tallied for the first 1.82 m, 100-hr fuels for the first 3.63 m, and 1000+-hr fuels for the entire 18.2 m. Live herbaceous fuels were sampled at 10 m and 20 m along the transect in a 30 cm by 30 cm quadrat placed 5 m to the right side of the main transect. All herbaceous fuels that were contained in the quadrat were clipped with pruning shears, placed in paper bags, oven-dried to a constant mass at 70°C, and weighed. Fuel bed height was measured to the nearest cm at three 30 cm intervals at 5, 10, and 15 m along the main transect. Duff and litter depth were measured to the nearest 0.1 cm at 5 and 15 m along each transect.

A hierarchical cluster classification method (Poulos et al. 2007, Poulos 2009) was used to assign each of the sampled plots to one of 40 standard Scott and Burgan fuel models (Scott and Burgan 2005). Each fuel model is characterized in part by a specific quantity of fuel loading and fuel bed depth across the 1-hr, 10-hr, 100-hr, and 1000+- hr live woody and live herbaceous fuel categories. For the cluster analysis, these fuel category quantities were used as centroids within a parameter space from which the Euclidean distance was calculated for each corresponding fuel category from the field plot data. Fuel models were then assigned to each of the field plots using the total minimum distance between the combination of all the fuel category centroids and plot measurements.

Creating and Evaluating a Custom Fuel Map from Landsat

To build a custom fuel map from my sampled field plots, Random Forest was used in Google Earth Engine (GEE) to create predictions of fuel models for each vegetation type across PTA. Random Forest is a non-parametric machine learning classifier that constructs multiple decision trees using randomly selected subsets of predictor variables in each tree (Breiman 2001). For this analysis, predictor variables in the resulting decision trees relied on the following input data: raw reflectance values from Landsat bands 2 through 11; vegetation types from Shaw and Castillo (1997); and fractional vegetation cover, vegetation height, elevation, leaf area index, mean annual temperature, mean annual precipitation, normalized difference vegetation index (NDVI), and enhanced vegetation index (EVI) from the Climate Atlas of Hawaii (Giambelluca et al. 2014). Landsat reflectance data were atmospherically corrected and normalized to at-surface reflectance using GEE functions.

The fuel model assignments from field plots (defined by the cluster classification; see above) were used as training data in the Random Forest classifier in GEE to predictively assign models across the PTA landscape to create a custom fuel map. The classifier was used to grow 500 decision trees, using 4 of the possible 18 variables randomly selected per tree. The final classification for the custom fuel map was then based on a majority vote from all 500 trees. The accuracy of the new custom fuel map was assessed using the out-of-bag error estimates (Liaw and Wiener 2002). To calculate out-of-bag error rates, when each decision tree is constructed using a bootstrap sample from the original data, about one-third of the data are kept aside as a validation dataset. Each tree can then be tested with samples not used in building that tree, creating an internal error estimate as the Random Forest classifier is built. Out-of-bag error estimates have been shown to be an unbiased internal estimate of test set error, providing a reliable indicator of classification accuracy similar to using a separate set of validation points of similar size to the training set.

The custom fuel map was compared to the LANDFIRE fuel model product for the study area by comparing fuel model assignments. Additionally, to assess how often the Random Forest classifier assigned the correct fuel model for the custom fuel map compared to the LANDFIRE product, the Random Forest classifier was run in a similar manner but with the use of the standard LANDFIRE fuel model assignments at field plots as training data. This provides an additional indicator of how well the cluster classification of fuel models can be extrapolated to a landscape level. I also tested the accuracy of fuel maps created using both types of training plots (those derived from the cluster classification vs. the standard LANDFIRE fuel model assignments), but withheld all plots that were classified as non-burnable fuel model types from the Random Forest classifier in order to assess the impact of PTA's unique lava surface on fuel mapping accuracy.

Results

Field Plots and Cluster Classification

Field measured 1-hr fuel loads ranged from 0.1 Mg ha^{-1} in sparse *Metrosideros* treeland to 1.0 Mg ha^{-1} in *Chenopodium* shrubland; 10-hr loads ranged from 0.1 Mg ha^{-1} in sparse *Metrosideros* treeland to 2.9 Mg ha^{-1} in *Sophora* shrubland; 100-hr loads ranged from 0.9 Mg ha^{-1} in *Chenopodium* Shrubland to 12.3 Mg ha^{-1} in *Sophora* shrubland; and 1000-hr loads ranged from 0 Mg ha^{-1} in a number of vegetation types to 6.8 Mg ha^{-1} in *Sophora* shrubland. Herbaceous fuel loads ranged from 0 Mg ha^{-1} in *Chenopodium* shrubland to 6.1 Mg ha^{-1} in *Dodonaea* shrubland. Total fuel loads by vegetation ranged from 2.0 Mg ha^{-1} in *Styphelia*-*Dodonaea* shrubland to 23.4 Mg ha^{-1} in *Sophora* shrubland. There was also large variation in fuel bed depth, ranging from 0.01 m in *Styphelia*-*Dodonaea* shrubland to 0.52 cm in *Dodonaea* shrubland (Table 1).

Fuel models assigned by the cluster classifier spanned 15 different Scott and Burgan model types ((Scott and Burgan 2005); Tables 2 and 3). The standard LANDFIRE fuel map contained 18 model types in the study area. However, the cluster classification method in assigning fuel model types resulted in different fuel model types that were not present in the standard LANDFIRE fuel map, and the LANDFIRE fuel product also had several fuel model types that were not present in the custom fuel map. The unique fuel models assigned to the custom fuel map tended to be lower fuel load models, while unique fuel models assigned to the LANDFIRE fuel map tended to be higher fuel load models. For the custom fuel map these models were GR5 (a grass fuel type), GS1 and GS2 (grass-shrub fuel types), SH1 (a shrub fuel type), and TU1 (a timber understory fuel type); and for the LANDFIRE fuel map these models were GR7 (a grass fuel type), GS4 (a grass-shrub fuel type), SH4, SH6, SH8, and SH9 (shrub fuel types), and TL3 and TL8 (timber litter fuel types). Many plots were assigned by the cluster classification to the NB9 fuel model ("barren" per Scott and Burgan (2005)) despite lying in areas mapped as vegetated. The custom fuel map consisted of 25% grass fuel models, 4% grass-shrub fuel models, 1%

shrub fuel models, 7% timber understory fuel models, and 63% non-burnable fuel models. The LANDFIRE fuel map consisted of 13% grass fuel models, 2% grass-shrub fuel models, 21% shrub fuel models, 10% timber litter fuel models, and 53% non-burnable fuel models.

Custom Fuel Map

The custom fuel map and the LANDFIRE fuel map assigned NB9 (barren) to a majority (63% and 65% respectively) of PTA's 53,000 ha (Table 4), with the custom fuel map estimating an additional 1,249 ha of model NB9. Specifically, NB9 was assigned to 88% (22 out of 25 plots) of Sparse *Metrosideros* treeland and to 90% (18 out of 20 plots) of *Styphelia-Dodonaea* shrubland in the custom fuel map. Conversely, 35% to 37% of this landscape were assigned fuel models that corresponded to burnable fuel types, with high potential for rates of wildfire spread and flame lengths. With respect to rates and lengths, burnable areas ranged from low (models GR1, GS1, SH1 and TU1) to very high (models GS4 and SH7) fire danger fuel conditions (Table 2). When the total fuel load based on standard fuel parameters for the Scott and Burgan fuel models were calculated for the custom fuel map, the study area contained 116,000 Mg ha^{-1} of total fuel load, compared to 434,000 Mg ha^{-1} of total fuel load for the LANDFIRE fuel map (Table 3). When the live woody fuel component (only available to burn in extreme weather and fire conditions) was withheld from this calculation, the custom fuel map contained 97,000 Mg ha^{-1} of total fuel load, and the LANDFIRE fuel map contained 270,000 Mg ha^{-1} of total fuel load.

Overall accuracy of the custom fuel map (Figure 1) using Random Forest out-of-bag error rates was 58% and the kappa score was 0.42 (Table 4). To assess the product against a national standard, the LANDFIRE data was compared with the custom fuel map by their fuel model designations, with an overall accuracy of 30% and a kappa score of 0.14. When plots that were designated as non-burnable by the cluster classification were withheld from Random Forest training, accuracy of the custom fuel map dropped to 32%, while accuracy of the LANDFIRE-derived fuel map dropped to 27%. When plots that were designated as non-burnable by the LANDFIRE map were withheld from training, accuracy of the custom fuel map dropped to 44%, while accuracy of the LANDFIRE-derived fuel map dropped to 29%. Variable importance plots, which estimate the mean decrease in accuracy that the exclusion of a particular variable has on classification accuracy, showed NDVI, EVI, and bands 10, 11, and 6 as being important predictors for the custom fuel map (Figure 2).

Discussion

The fuels landscape of PTA is highly heterogeneous, with average total fuel loading in sampled plots ranging from 0.0 Mg ha^{-1} to 20 Mg ha^{-1} across 15 to 18 distinct fuel model types in both the LANDFIRE and custom fuel map. The accuracy assessments demonstrate that LANDFIRE did not align with the fuel model assignments of the custom fuel map (30% accuracy). In contrast, the custom fuel map demonstrated a higher mapping accuracy of 58%. This accuracy compares favorably with accuracies from other studies that have predicted fuel models from remotely sensed data, which have ranged from 50% to 85% (Peterson et al. 2012).

Improvements in the custom fuel map over LANDFIRE included better discernment of fuel beds that lie on the threshold of being able to carry fire. The custom fuel map classified plots capable of carrying fire as low fuel load models, while these plots were classified as non-burnable models in the standard LANDFIRE fuel map. The custom fuel map also improved accuracy by assigning a non-burnable fuel model to plots that were classified as various shrub and forest fuel models that were nevertheless incapable of carrying fire based on fuel loading (e.g., woodland plots that have a high amount of exposed substrate yet support a scattered tree and shrub overstory). In addition to differences in fuel model assignments, the custom classification method tended to assign fuel models that were lower in total fuel loads than the LANDFIRE map. This resulted in total fuel loads across the study area that were three to four times less than that of the LANDFIRE map (Table 3).

The 40 fuel models described by Scott and Burgan (2005) that are used as a basis for the LANDFIRE product and for the custom fuel map are based on empirical observations of fuel characteristics and wildfire behavior. While fuel models present in the custom fuel map and the LANDFIRE product were commonly given descriptions based on vegetation from the continental United States (i.e. SH3 and SH4 with a potential "pine overstory"), their importance for Hawaii serves in how well it translated into describing potential wildfire behavior, at least until more custom fuel models are developed for specific use in Hawaii (Beavers 2001). Plots with the vegetation cover of Sparse *Metrosideros* treeland and *Styphelia-Dodonaea* shrubland were frequently classified as NB9 in the custom fuel map, versus GR1, GS1, SH1 and TU1 (low fuel load classifications) in the LANDFIRE product. In total, an additional 4,857 ha were classified as NB9, or 9% of the study area. While these plots contained vegetation of the described type, both vegetation and fuels were negligible to the point where wildfire would not carry through the area represented by the plot (Figure 3). As a descriptor of potential wildfire behavior, NB9 serves as a more accurate characterization of these plots from the standpoint of wildfire management.

When plots classified as non-burnable were withheld from the list of training plots, the accuracy of cluster classification decreased by half, while the Random Forest model trained on LANDFIRE classifications decreased in accuracy by several percentage points. Improvements in discerning burnable and non-burnable plots contributed to an improved classification accuracy for the custom fuel map. Because LANDFIRE fuel maps are frequently used to model pixel-to-pixel fire spread, the presence of pixels classified as non-burnable likely result in poor estimates of fire intensity and, in particular, rates of spread, and thus poor estimates of fire risk.

The custom fuel map diverged from the LANDFIRE product first in the cluster classification of fuel model types, and then further in the Random Forest classification of the study area. By assigning plots to fuel models based on a statistical relationship with each individual fuel loading component (1-hr, 10-hr, etc.), various fuel models were selected that were not present in the LANDFIRE fuel map, which contributed to disagreement between classifications. The hierarchical cluster classification method likely avoided uncertainties involved in assigning fuel models based on expert opinion and predicted wildfire behavior (Poulos et al. 2007, Poulos 2009). This reduction in bias may have been reflected when mapped at the landscape level using Random Forest. The Random Forest classifier mapped the cluster fuel assignments with 58% validation accuracy based on out-of-bag error rates, while the mapped plot-level LANDFIRE fuel assignments showed only a 30% validation accuracy. This may be due to a more robust relationship between sampled fuel component loadings and the assigned fuel model from field sampling for the custom fuel map, or the assigned fuel model and relevant biophysical predictors and remote sensing.

Variable importance plots identified NDVI as the most important predictor variable, which is in line with many previous studies which demonstrated this vegetation index to be an important predictor in differentiating between fuel models at the landscape level (Peterson et al. 2012), and in predicting canopy fuel characteristics (Rollins et al. 2004, Pierce et al. 2012). Conversely, predictor variables that were not derived from vegetation indices or Landsat bands, such as rainfall and elevation, were not found to be important. The importance of NDVI, a predictor variable sensitive to properties such as rainfall and productivity, is particularly relevant due to certain limitations of this study. Sampling took place during one constrained period of time and, as such, was not able to capture temporal variability in fuel loads. Nonnative grass fuel loading and fuel moistures in Hawaii have been found to have high intra-annual variability (Ellsworth et al. 2013). Landsat bands and predictor variables such as NDVI, however, have been shown capable of differentiating between fuel classes based on vegetation phenology (Riaño et al. 2002, Van Wagtendonk and Root 2003). With additional sampling across time, a more accurate fuel map based on the Random Forest classifier may be possible. For reference, total fuel loads in field plots sampled in *Eragrostis* grasslands in PTA in the summer of 2016, after a prolonged multi-year drought, averaged 4.6 Mg ha^{-1}, compared to 5.3 Mg ha^{-1} in this study, highlighting the importance of recent weather in determining fuel loads in this vegetation type. In turn, total fuel loads in field plots sampled in sparse *Metrosideros* treelands in 2016 averaged 2.3 Mg ha^{-1}, compared to 2.3 Mg ha^{-1} in this study, highlighting the predominance of woody fuels in this vegetation type that do not vary over short time periods.

The custom fuel map produced here, while reliable by statistical measures, is based on wildfire behavior fuel models developed for the continental United States (Scott and Burgan 2005). While these models can work well in certain situations in the Hawaiian Islands (Pierce et al. 2014), it is clear that fuel conditions in other parts of the Islands are not only highly variable (Ellsworth et al. 2013) but also produce wildfire behavior that is outside the ability of standard wildfire behavior models to reproduce (Beavers 2001, Benoit et al. 2010). Until validated fuel models exist for the types of tropical vegetation found in Hawaii, fuel models developed for the continental United States will likely continue to be applied with less than perfect results, demonstrating a need to be flexible in choice of tools for wildfire and fuel modeling. Future studies should focus on testing custom fuel models, including physics-based wildfire models (Mell et al. 2007) and probabilistic approaches (Preisler et al. 2004, Trauernicht 2019), for their effectiveness in the Hawaiian Islands. Additionally, new custom fuel maps can potentially be validated by hindcasting historical wildfires to compare actual and simulated burn perimeters and wildfire behavior (Krasnow et al. 2009), as well as wildfire severity (Pierce et al. 2012).

Although wildfire simulations were beyond the scope of the present analysis, the disparities between the custom fuel map and the standard LANDFIRE fuel map indicate the value of integrating sampled field data, biophysical predictors, and remote sensing into mapping efforts for wildfire management. More accurate fuel mapping will necessarily rely on field data. However, hierarchical cluster classification of sampled field data into standard fuel models can greatly improve fuel model classifications that represent on-the-ground fuel conditions, which leads to more accurate mapping at the landscape level. GEE's continuously updated catalog of Landsat data, as well as newer high-resolution platforms such as Sentinel, offers the opportunity to rapidly update custom fuel maps that take into account recent disturbances and vegetation responses to weather events and land use change. The classification approach presented here can be used to fit local fuel characteristics with standard fuel models to generate more accurate fuel maps, providing an effective and accessible means to extrapolate from spatially and temporally limited field data.

Table 1. Summary of fuel loading (+/- 1 S.D.) at Pōhakuloa Training Area (PTA) on the Island of Hawaii.

Vegetation Community	n	1-hr Fuels (Mg ha-1)	10-hr Fuels (Mg ha-1)	100-hr Fuels (Mg ha-1)	1000-hr Fuels (Mg ha-1)	Herbaceous Fuels (Mg ha-1)	Total Fuels (Mg ha-1)	Fuel Bed Depth (cm)
Chenopodium Shrubland	1	1.02 +/- 0	2.26 +/- 0	0.9 +/- 0	0 +/- 0	0 +/- 0	4.18 +/- 0	22.57 +/- 0
Disturbed	2	0.17 +/- 0.15	0.34 +/- 0	0 +/- 0	0 +/- 0	0.04 +/- 0.02	0.54 +/- 0.17	1.98 +/- 1.6
Dodonaea Shrubland	12	0.36 +/- 0.26	0.6 +/- 0.57	1.06 +/- 1.27	0 +/- 0	6.07 +/- 4.37	8.09 +/- 4.76	52.19 +/- 21.65
Eragrostis Grassland	4	0.69 +/- 0.61	1.56 +/- 1.28	2.72 +/- 2.22	0 +/- 0	0.3 +/- 0.58	5.26 +/- 4.29	15.31 +/- 20.05
Myoporum Shrubland	17	0.48 +/- 0.46	1.66 +/- 1.31	8.83 +/- 7.98	2.78 +/- 4.74	1.38 +/- 1.62	15.20 +/- 12.52	30.56 +/- 26.23
Open *Metrosideros* Treeland	31	0.34 +/- 0.3	1.41 +/- 1.46	6.53 +/- 4.86	2.11 +/- 2.33	1.29 +/- 1.69	11.68 +/- 7.60	21.1 +/- 17.59
Cenchrus Grassland	2	0.19 +/- 0.27	1.94 +/- 2.74	1.36 +/- 0.65	0 +/- 0	4.88 +/- 6.9	8.38 +/- 3.24	43.18 +/- 49.09
Sophora Shrubland	9	0.62 +/- 0.78	2.93 +/- 3.33	12.26 +/- 16.88	6.75 +/- 19.29	0.81 +/- 0.91	23.38 +/- 35.72	23.92 +/- 22.04
Sparse *Metrosideros* Treeland	20	0.08 +/- 0.12	0.08 +/- 0.16	0.91 +/- 1.77	1.18 +/- 4.25	0.01 +/- 0.02	2.25 +/- 5.08	1.74 +/- 3.58
Styphelia-Dodonaea Shrubland	25	0.16 +/- 0.21	0.24 +/- 0.55	0.54 +/- 1.17	1.03 +/- 4.27	0 +/- 0.01	1.97 +/- 5.19	1.31 +/- 1.53

Table 2. Description of fuel models present in the custom fuel map and in the standard LANDFIRE fuel map at Pōhakuloa Training Area (PTA) on the Island of Hawaii (Scott and Burgan 2005).

Model	Description
GR1	Short, sparse dry climate grass is short, naturally or heavy grazing
GR2	Low load, dry climate grass primarily grass with some small amounts of fine, dead fuel
GR3	Low load, very coarse, humid climate grass continuous, coarse humid climate grass
GR4	Moderate load, dry climate grass, continuous, dry climate grass, fuelbed depth about 2 feet
GR5	Low load, humid climate grass, fuelbed depth is about 1-2 feet
GR6	Moderate load, continuous humid climate grass, not so coarse as GR5
GR7	High load, continuous dry climate grass, grass is about 3 feet high
GS1	Low load, dry climate grass-shrub shrub about 1 foot high, grass load low
GS2	Moderate load, dry climate grass-shrub, shrubs are 1-3 feet high, grass load moderate
GS3	Moderate load, humid climate grass-shrub, moderate grass/shrub load, grass/shrub depth is less than 2 feet
GS4	High load, humid climate grass-shrub, heavy grass/shrub load, depth is greater than 2 feet
NB1	Urban
NB9	Barren
SH1	Low load dry climate shrub, woody shrubs and shrub litter, fuelbed depth about 1 foot, may be some grass,
SH2	Moderate load dry climate shrub, woody shrubs and shrub litter, fuelbed depth about 1 foot, no grass
SH3	Moderate load, humid climate shrub, woody shrubs and shrub litter, possible pine overstory, fuelbed depth 2-3 feet
SH4	Low load, humid climate timber shrub, woody shrubs and shrub litter, low to moderate load, possible pine overstory, fuelbed depth 3 feet
SH5	High load, humid climate grass-shrub combined, heavy load with depth greater than 2 feet
SH6	Low load, humid climate shrub, woody shrubs and shrub litter, dense shrubs, little or no herbaceous fuel, depth about 2 feet
SH7	Very high load, dry climate shrub, woody shrubs and shrub litter, very heavy shrub load, depth 4-6 feet
SH8	High load, humid climate shrub, woody shrubs and shrub litter, dense shrubs, little or no herbaceous fuel, depth about 3 feet
SH9	Very high load, humid climate shrub, woody shrubs and shrub litter, dense finely branched shrubs with fine dead fuel, 4-6 feet tall, herbaceous may be present
TL3	Very high load, humid climate shrub, woody shrubs and shrub litter, dense finely branched shrubs with fine dead fuel, 4-6 feet tall, herbaceous may be present
TL8	Long needle litter, moderate load long needle pine litter, may have small amounts of herbaceous fuel
TU1	Low load dry climate timber grass shrub, low load of grass and/or shrub with litter
TU3	Moderate load, humid climate timber grass shrub, moderate forest litter with some grass and shrub

Table 3. Summary of extent of fuel model types across Pōhakuloa Training Area (PTA) on the Island of Hawaii for the custom and LANDFIRE fuel maps.

Custom Fuel Map	Area (ha)	Fuel Load (Mg ha^{-1})	LANDFIRE Fuel Map	Area (ha)	Fuel Load (Mg ha^{-1})	Total Overlap Area (ha)
GR1	450	404	**GR1**	365	327	32
GR2	1416	3492	**GR2**	564	1391	41
GR3	1879	8424	**GR3**	3344	14992	645
GR4	8665	41762	**GR4**	1	5	
GR5	855	5558	GR5		0	
GR6	373	2927	**GR6**	2726	0	194
GR7		0	**GR7**	41	588	
GS1	98	297	GS1		0	
GS2	71	414	GS2		0	
GS3	2166	15780	**GS3**	94	0	
GS4		0	**GS4**	1174	33686	
NB1	668	0	**NB1**	668	0	
NB9	32814	0	**NB9**	27957	0	26899
SH1	22	96	SH1		0	
SH3	310	6706	**SH3**	112	2423	
SH4		0	**SH4**	2574	27408	
SH6		0	**SH6**	43	554	
SH8		0	**SH8**	972	23206	
SH9		0	**SH9**	7593	263829	
TL3		0	**TL3**	5271	64988	
TL8		0	**TL8**	4	74	
TU1	3014	24999	TU1		0	
TU3	710	5173	**TU3**	6	44	
Total Hectares	53510			53510		27811

Table 4. Confusion matrix of Random Forest of cluster classification at Pōhakuloa Training Area (PTA) on the Island of Hawaii.

	GR1	GR2	GR3	GR4	GR5	GR6	GS1	GS2	GS3	NB9	SH1	SH3	TU1	TU3	Total Actual	Percent Correct
GR1	1	0	0	0	0	0	0	0	0	5	0	0	3	0	9	0.111111
GR2	1	1	0	0	0	0	1	0	0	1	0	1	1	0	6	0.166667
GR3	0	0	3	1	0	0	0	0	0	0	0	0	1	0	5	0.6
GR4	0	0	0	2	0	0	0	0	1	0	0	0	0	0	3	0.666667
GR5	0	0	0	1	0	0	0	0	0	0	1	0	0	0	2	0
GR6	0	0	0	0	1	0	0	0	0	0	0	1	0	0	2	0
GS1	0	0	0	0	0	0	0	1	0	1	0	0	1	0	3	0
GS2	0	1	0	0	0	0	0	1	0	0	0	0	1	0	3	0.333333
GS3	0	0	0	1	0	0	0	0	3	1	0	0	1	0	6	0.5
NB9	0	1	0	0	0	0	0	0	1	54	0	0	3	0	59	0.915254
SH1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
SH3	0	0	0	1	0	1	0	0	0	0	0	0	0	0	2	0
TU1	1	0	1	0	0	0	0	1	0	7	0	0	7	0	17	0.411765
TU3	0	0	0	0	0	0	0	0	0	1	0	0	3	0	4	0
Total Predicted	1	1	3	2	0	0	0	1	3	54	0	0	7	0		0.59

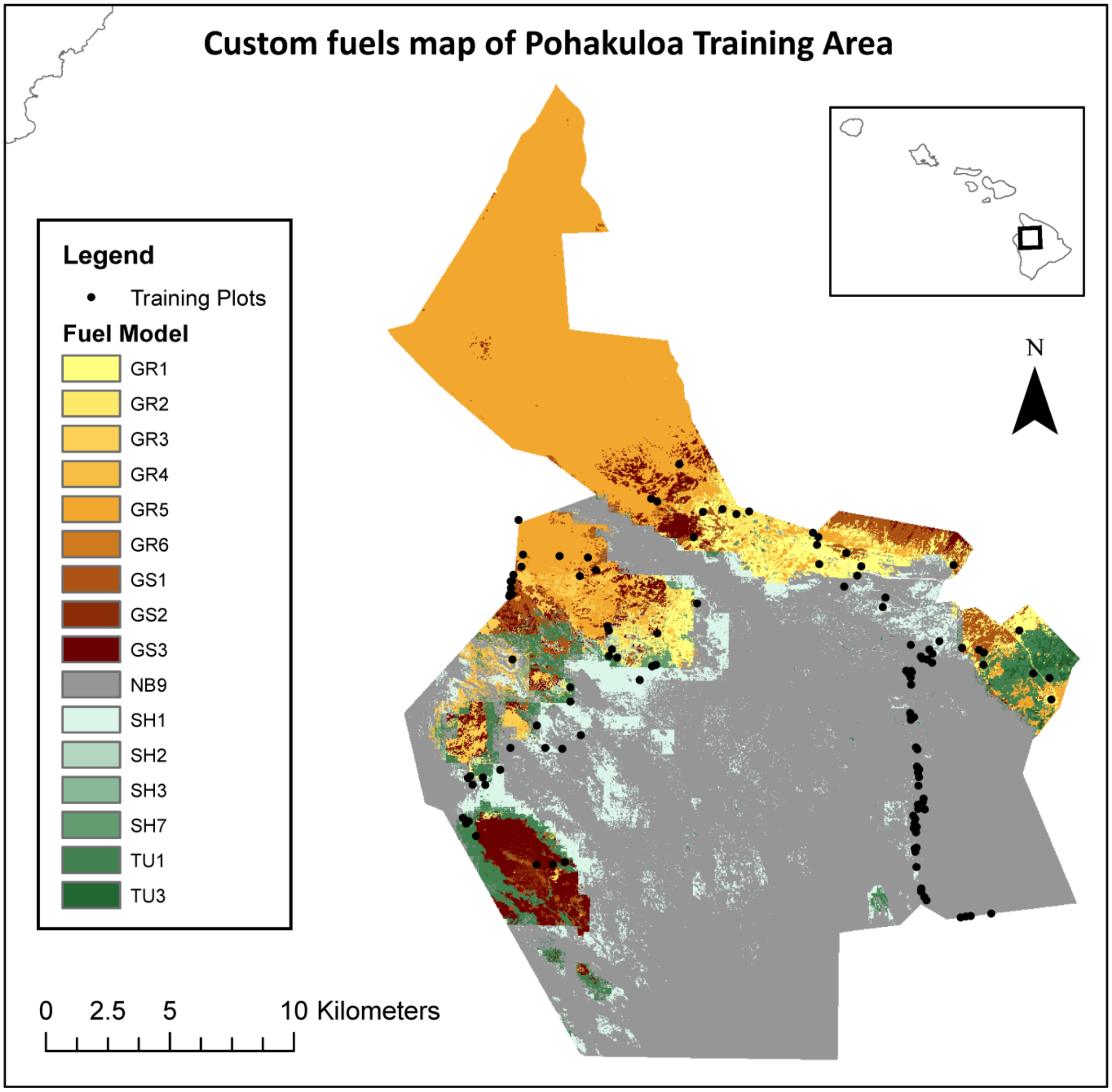

Figure 1. Custom fuel map of Pōhakuloa Training Area (PTA) on the Island of Hawaii derived from Random Forest classification of field sampled and cluster classified plots, environmental predictors, and Landsat 8 imagery. Fuel model types from Scott and Burgan (2005).

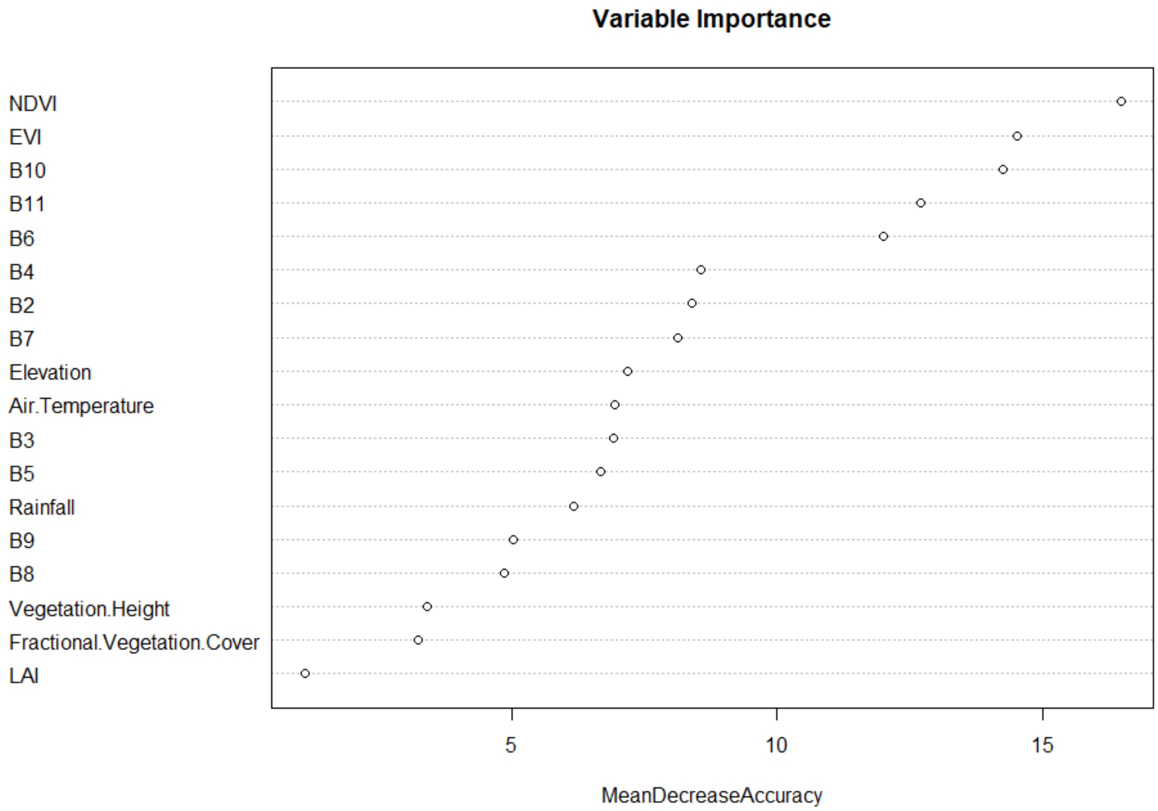

Figure 2. Variable importance plot of Random Forest classification for the custom fuel map at Pōhakuloa Training Area (PTA) on the Island of Hawaii.

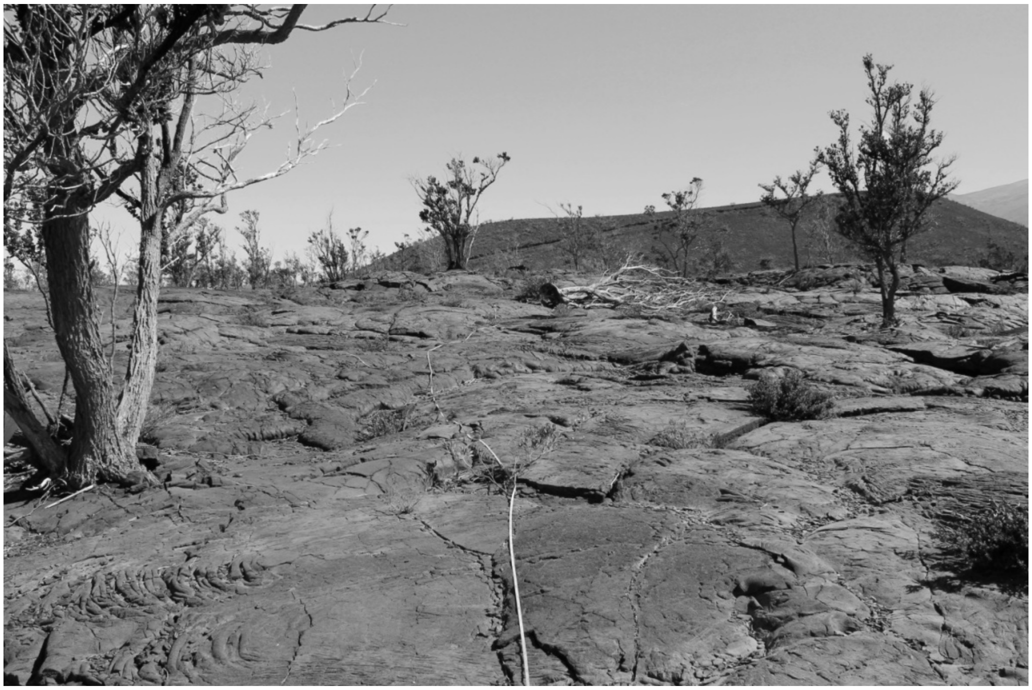

Figure 3. An example of a field plot in an area of Pōhakuloa Training Area (PTA) on the Island of Hawaii classified as Sparse *Metrosideros polymorpha* treeland by Shaw and Castillo (1997).

Chapter 4. Conclusions

The concept for the second chapter, '*Moisture availability regulates increases in fine fuels and modeled wildfire behavior following nonnative feral ungulate removal in Hawaii,'* was developed in response to a persistent question for wildfire management in Hawaii regarding what impacts the removal of nonnative feral ungulates has on fuels. The common assumption was that removal, absent any additional active management to reduce fuels, would result in substantial build-up of fuels that would create significant wildfire risk. Past research had focused on the impacts of nonnative feral ungulate removal on non-fuels characteristics of ecosystems, or on the impacts of domestic grazing on fuels (Stone et al. 1992, Kellner et al. 2011, Cole et al. 2012, Evans et al. 2015, Hess 2016). I found that nonnative feral ungulate removal resulted in an increase in fine fuel loads (grass and herbaceous fuels) and modeled wildfire behavior, with the magnitude of ungulate effects scaling linearly and positively with moisture. These results provide valuable insight into how climate and management factors drive potential fuel loading and wildfire behavior in critical management areas. However, it is important to bear in mind that these results represent only a portion of the total exclosures on a single island.

It is possible that other factors may affect fuel characteristics in ways not captured in this study, which warrant additional attention. These potential factors include vegetation palatability, foraging habits of different types of ungulates, seasonal controls on ungulate migration patterns, variations in ungulate densities, and prior level of degradation (Blackmore and Vitousek 2000, Cabin et al. 2000, Weller et al. 2011, Hess 2016). Furthermore, the majority of the sampling took place during the summer of a single year, while significant variability may exist in fuel loading due to seasonal differences or in response to extreme weather events (Ellsworth et al. 2013, Trauernicht 2019). One question of particular interest raised by potential fuel variability due to extreme weather events is whether there is an optimal climate window to remove nonnative feral ungulates from a system (e.g., before or after a La Niña or El Niño).

Ungulate removal has occurred on >750 km^2 of public land in the Hawaiian Islands, which is an area equivalent to half of the island of Oahu. Due to the size of many management units where nonnative feral ungulate removal occurs, efficient use of resources is critical. Fuel reduction treatments are better prioritized for mesic and wet environments after nonnative feral ungulate removal, due to the more substantial increases in fuel loads observed in these areas. Even moderately wet areas are of concern, as nonnative grasslands in Hawaii have demonstrated high intensity wildfire behavior in what would be considered benign weather conditions in the continental United States, such as high relative humidity and low wind (Trauernicht et al. 2015). Study sites on the wettest end of the precipitation gradient (~3200 mm yr^{-1}), for example, experienced multiple periods of moderate to extreme drought between 2000 and 2019 (Svoboda et al. 2002). Recent models of climate change in Hawaii predict that mesic zones will decrease in cover, with a subsequent increase in dry and wet zones (Selmants et al. 2017), which could shift peak wildfire risk to higher elevations with higher fuel loads (Trauernicht 2019). Climatic projections by Abatzoglou et al. (2018) of increased fuel aridity by mid-century will also potentially increase burned area, particularly in wet forests. As a result, increased fuel loading after ungulate removal in wet moisture zones may entail an even greater wildfire risk in the future. Anticipating such changes is critical for wildfire and ecosystem management.

Most sites in the study were chosen because they were not managed beyond the fencing and removal of nonnative feral ungulates. Many exclosures in the Hawaiian Islands are more actively managed, such as through fuels mitigation and ecological restoration, such that the implications of this study should be assessed with the understanding that other management actions may alter the impacts of nonnative feral ungulate removal on fuel loading and wildfire behavior (Trauernicht et al. 2015, Hess 2016). This current study found that in sites with active ecological restoration (e.g., outplanting of native species), fine fuel loading is reduced over time by as much as 41% after ten years.

While management actions such as mowing, thinning, green strips, managed grazing, and prescribed fire are among a number of potential fuels management strategies available for land managers to reduce fuel loads after ungulate removal (Trauernicht et al. 2015), active ecological restoration appears to provide a viable long-term reduction in fuel loads (Cabin et al. 2002, Ammondt and Litton 2012, Medeiros et al. 2014, Ellsworth et al. 2015). Ecological restoration plots that were sampled in this study required a high initial investment in outplanting and herbicide application (e.g., see Powell et al. (2017), Wada et al. (2017)). However, once outplants were established, little to no upkeep was required while factors such as canopy shade further reduced invasive grass fuel loads. This type of fuel reduction compares favorably compared to management actions such as mowing and prescribed fire which can require repeated applications, or managed grazing which is at odds with conversation objectives.

The third chapter, titled '*Random Forest fuel mapping across a heterogeneous dry tropical montane landscape,'* addressed another pressing wildfire management issue by assessing the validity of existing surface fuel maps in Hawaii. I incorporated field sampled fuel data with biophysical predictors, remote sensing, and Random Forest classification to create a custom landscape-level fuel map encompassing multiple vegetation types and compared it to LANDFIRE, a national set of geospatial fuel products and the only set of wall-to-wall fuel maps for the Hawaiian Islands. Mapping accuracy of the custom fuel map compared favorably with past similar mapping efforts of fuel models outside of Hawaii based on remotely sensed imagery (Peterson et al. 2012), with a 58% mapping accuracy. In turn, the custom fuel map was poorly correlated with the standard LANDFIRE fuel map, with only a 30% agreement, highlighting the need for custom fuel maps to more accurately inform wildfire management. Ultimately, overall accuracy and additional validation remains an issue and points towards a need for higher resolution studies of the fuels landscape in Hawaii. One question of interest in the classification approach in this study that was not fully answered is how variable sampled fuels in the Hawaiian Islands are over a multi-year to decadal timescale, and whether such variability affects fuel model designation. The answer to this requires repeat sampling across time and in various vegetation types, and accurate fuel mapping of this variability will likely depend on how well-correlated remote sensing and vegetation indices are with 1-hr and 10-hr fuels. The classification approach presented here, regardless, can be used in any area where limited data are available to generate more accurate fuel maps.

Future work building on this research in the Hawaiian Islands and on other tropical Pacific Islands should focus on: the interaction and efficacy of different management strategies for reducing fine fuel loads after the exclusion of nonnative feral ungulates; the impact of extreme weather events, such as droughts or pluvials, on fuels after nonnative feral ungulate removal; the interactive effects of nonnative feral ungulate removal and predicted climate change on fuels and modeled wildfire behavior; the validation of alternative fuel and fire behavior models; and the continued development and validation of very-high-resolution satellite imagery and machine learning to predictively map fuels to improve wildfire management.

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